Skip all front matter: Jump to Page 1

Report Documentation Page

Form Approved
OMB No. 0704-0188

1. REPORT DATE **2014**	2. REPORT TYPE	3. DATES COVERED **00-00-2014 to 00-00-2014**
4. TITLE AND SUBTITLE **The Effectiveness of Remotely Piloted Aircraft in a Permissive Hunter-Killer Scenario**		5a. CONTRACT NUMBER 5b. GRANT NUMBER 5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)		5d. PROJECT NUMBER 5e. TASK NUMBER 5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **RAND Corporation,Project Air Force,1776 Main Street, PO Box 2138,Santa Monica,CA,90407-2138**		8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)		10. SPONSOR/MONITOR’S ACRONYM(S) 11. SPONSOR/MONITOR’S REPORT NUMBER(S)
12. DISTRIBUTION/AVAILABILITY STATEMENT **Approved for public release; distribution unlimited**		
13. SUPPLEMENTARY NOTES		
14. ABSTRACT		
15. SUBJECT TERMS		

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**	**Same as Report (SAR)**	**71**	

This report is part of the RAND Corporation research report series. RAND reports present research findings and objective analysis that address the challenges facing the public and private sectors. All RAND reports undergo rigorous peer review to ensure high standards for research quality and objectivity.

Research Report

The Effectiveness of Remotely Piloted Aircraft in a Permissive Hunter-Killer Scenario

Lance Menthe, Myron Hura, Carl Rhodes

RAND CORPORATION

Research Report

The Effectiveness of Remotely Piloted Aircraft in a Permissive Hunter-Killer Scenario

Lance Menthe, Myron Hura, Carl Rhodes

RAND Project AIR FORCE

Prepared for the United States Air Force
Approved for public release; distribution unlimited

RAND CORPORATION

The research described in this report was sponsored by the United States Air Force under Contract FA7014-06-C-0001. Further information may be obtained from the Strategic Planning Division, Directorate of Plans, Hq USAF.

Library of Congress Cataloging-in-Publication Data

Menthe, Lance.
The effectiveness of remotely piloted aircraft in a permissive hunter-killer scenario / Lance Menthe, Myron Hura, Carl Rhodes.
pages cm
Includes bibliographical references.
ISBN 978-0-8330-8397-5 (pbk. : alk. paper)
1. Drone aircraft—United States. 2. Air warfare—United States. I. Hura, Myron, 1943- II. Rhodes, Carl, 1970- III. Title..

UG1242.D7M45 2014
358.4'24—dc23

2014005070

The RAND Corporation is a nonprofit institution that helps improve policy and decisionmaking through research and analysis. RAND's publications do not necessarily reflect the opinions of its research clients and sponsors.

Support RAND—make a tax-deductible charitable contribution at www.rand.org/giving/contribute.html

RAND OFFICES

SANTA MONICA, CA • WASHINGTON, DC

PITTSBURGH, PA • NEW ORLEANS, LA • JACKSON, MS

BOSTON, MA • CAMBRIDGE, UK • BRUSSELS, BE

www.rand.org

Preface

The research presented in this report is part of a larger project that examined the effectiveness of several notional design concepts for remotely piloted aircraft (RPA). Here, we present in detail the analysis of a permissive hunter-killer mission.

The analysis used in this research was performed using the RAND Corporation's agent-based Systems and Concept of Operations (CONOPS) Operational Effectiveness Model (SCOPEM), which functions within the Air Force's agent-based System Effectiveness Analysis Simulation (SEAS) modeling environment.[1] RAND developed additional modeling capabilities for SCOPEM during fiscal years 2009 and 2010 to enable this work.[2] This report also serves to document these capabilities and the methodology in general.

This research was sponsored by Randall Walden (SAF/AQI), Lt Gen James (AF/A2), and Maj Gen Andersen (Air Force Intelligence, Surveillance, and Reconnaissance Agency). The work was conducted within the Force Modernization and Employment Program of RAND Project AIR FORCE as part of a fiscal year 2011 study, "Developing an Analytically Based Vision for Air Force Capabilities Delivered by Remotely Piloted Aircraft." It should be of interest to those interested in the trade-offs between different RPA design concepts and to those working more generally in the fields of agent-based modeling and simulation.

RAND Project AIR FORCE

RAND Project AIR FORCE (PAF), a division of the RAND Corporation, is the U.S. Air Force's federally funded research and development center for studies and analyses. PAF provides the Air Force with independent analyses of policy alternatives affecting the development, employment, combat readiness, and support of current and future air, space, and cyber forces. Research is conducted in four programs: Force Modernization and Employment; Manpower, Personnel, and Training; Resource Management; and Strategy and Doctrine.

Additional information about PAF is available on our website:

http://www.rand.org/paf/

---

[1] Lance Menthe and Jeffrey Sullivan, *A RAND Analysis Tool for Intelligence, Surveillance, and Reconnaissance: The Collections Operations Model*, Santa Monica, Calif.: RAND Corporation, TR-557-AF, 2008.

[2] Sherrill Lingel, Lance Menthe, Brien Alkire, John Gibson, Scott A. Grossman, Robert A. Guffey, Keith Henry, Lindsay D. Millard, Christopher A. Mouton, George Nacouzi, and Edward Wu, *Methodologies for Analyzing Remotely Piloted Aircraft in Future Roles and Missions*, Santa Monica, Calif.: RAND Corporation, DB-637-AF, 2012.

Contents

Figures

Tables

Summary

Introduction

Remotely piloted aircraft (RPAs)—notably the medium-altitude MQ-1 Predator and MQ-9 Reaper—have provided crucial support to counterinsurgency and counterterrorism operations over the past decade. As these operations come to a close, the Air Force has begun to evaluate additional RPA concepts to meet future needs.

In this report, we analyze the operational effectiveness of three RPA design concepts, plus the MQ-9 as a baseline, on a "hunter-killer" mission: to find and destroy a specific moving vehicle. All the findings in this report are based on the modeling results for a particular scenario (with variants) and should be understood within that context.

Assumptions

Although our scenario is representative of many hunter-killer missions as they are executed today, it is not representative of others. It also relies on several crucial assumptions. Most important, the threat environment we modeled is permissive, meaning that there is negligible threat to the aircraft. This permits the use of concepts of operations (CONOPS) untempered by survivability concerns.

In the particular scenario we considered, the initial cue for the target vehicle is urgent but imprecise, allowing only that the enemy is expected to emerge from hiding somewhere in a five nmi^2 area within 15 minutes. Its ultimate destination is believed to be outside this area but is otherwise unknown. Finding the target vehicle before it leaves the area therefore necessitates a rapid, brute-force search.

Because the area is not especially large, the search is not difficult but is complicated by environmental factors. The cued area is an urban environment, which constrains line of sight to steep viewing angles. Moreover, in many of the variants we considered, the RPA sensor operator is forced to contend with other effects detrimental to establishing and maintaining line of sight, including fog and clouds. The parameters of the initial cue, as described above, were selected to highlight how these environmental conditions affect operational effectiveness.

The rules of engagement and CONOPS we selected are also fairly restrictive. They require that the target be positively identified with full-motion video (FMV) and that the RPA sensor operator keep the target in view with FMV whenever weather conditions permit. This places a high burden on the required resolution of the imagery, which must yield an estimated National

Imagery Interpretability Rating Scale (NIIRS) quality level of 7.0 or 8.0.[3] (Both cases are modeled.) While reflective of current practice, these requirements effectively relegate ground moving target indication (GMTI) to a lesser role than it could otherwise play. These requirements also preclude the RPA from flying at higher altitudes, which in turn reduces the effective ground coverage area that the RPA sensor operator can achieve. The rules of engagement therefore force the RPA pilot to choose a flight profile that balances the competing demands for high resolution and greater ground coverage area.

We made several simplifying operating assumptions as well. We did not consider the possibility of communications jamming or loss of Global Positioning System connectivity, either of which could potentially be devastating. We assumed that each RPA had sufficient communications capacity and processing, exploitation, and dissemination resources to fulfill its mission—a necessary but admittedly heroic assumption mandated largely by certain technical limitations. Finally, while the enemy is allowed some awareness that it is in danger of being watched, we assumed that it could neither see nor hear the RPA. The target vehicle also does not employ camouflage, concealment, or any of the other clever ruses that have at times been observed in the field: The only adaptive enemy behavior is to come to a halt from time to time, in an attempt to confuse possible GMTI tracking.

These choices and assumptions enabled us to avoid certain issues so that we could focus instead on the broader trade-offs between platform size and number; sensor performance; and the complicating effects of darkness, fog, and cloud cover. However, they also inherently limit the applicability of our findings regarding these trade-offs. Nevertheless, we believe that our analysis illuminates some important, basic considerations in RPA design choices. It also demonstrates a successful analytical methodology that may be expanded to address more-challenging scenarios.

Design Concepts

The RPA design concepts we considered are meant to represent typical parameters for what the Air Force defines today as “Group 3,” “Group 4,” and “Group 5” classes of RPAs, with operational performance and sensor packages comparable to those of today’s aircraft with similar size, weight, and power.[4] These designs reflect what is currently practical rather than what may

---

[3] For a description of the NIIRS scale, see Jon Leachtenauer, William Malia, John Irvine, Linda Colburn, and Nanette Salvaggio, “General Image-Quality Equation: GIQE,” *Applied Optics*, Vol. 36, No. 32, November 10, 1997.

[4] These groups are categorized roughly as follows. Group 3 is anywhere in the large range of 56–1,320 lbs., less than 250 knots indicated airspeed, and an operating altitude below 18,000 ft. above mean sea level (MSL). Group 4 is anything greater than 1,320 lbs., at any airspeed, with the same restriction on operating altitude as for Group 3. Group 5 is the same as Group 4 but with an operating altitude above 18,000 MSL (U.S. Department of Defense, *Unmanned Systems Integrated Roadmap FY 2011–2036*, Washington, D.C., November 9, 2011b, p. 12, Figure 1). As is evident, these definitions are very broad. They span the space of possibilities but only because they specify so little. Future research on more-advanced RPA concepts would benefit from a richer nomenclature.

be possible in the future. Table S.1 outlines the configurations of these designs, with the MQ-9 parameters we used for comparison.

Modeling Approach

The analysis in this report used RAND's Systems and CONOPS Operational Effectiveness Model (SCOPEM), an interlocking suite of sensor, environment, and platform modules built within the Air Force's agent-based System Effectiveness Analysis Simulation (SEAS) modeling environment.[5] SEAS is part of the Air Force Standard Analysis Toolkit. Using this model, we performed a Monte Carlo analysis of each of the 144 variants we considered.

Modeling Results

The modeling results may be summarized briefly in two charts. They show how the operational effectiveness of each RPA design concept varies by illumination (day versus night), weather (clear, fog, or clouds), number of platforms (one versus three),[6] and using different thresholds for positive identification of the target vehicle (NIIRS 7.0 versus NIIRS 8.0). Figure S.1 below shows the probability that the target vehicle was successfully identified. Figure S.2 shows how often the target vehicle was also successfully followed all the way to the kill zone. (Note that the second is contingent on the first.)

Table S.1. RPA Design Concepts

Concept	Payload (lbs.)	Cruise Speed (knots)	Electro-Optical and Infrared FMV Sensor	GMTI and Synthetic Aperture Radar Sensor
MQ-9 Reaper	3,850[a]	180[b]	MTS-B	Lynx
Group 5	4,000	360	MTS-B	Lynx
Group 4	535	125	Raven Eye II	—
Group 3	35	70	Raven Eye I	—

[a] Includes 850 lbs. internal and 3,000 lbs. external payload capacity.
[b] The actual cruise speed varies. We selected this figure for consistency of analysis with other parts of the study.

---

5 Formerly known as the Collections Operations Model. See Lance Menthe and Jeffrey Sullivan, *A RAND Analysis Tool for Intelligence, Surveillance, and Reconnaissance: The Collections Operations Model*, Santa Monica, Calif.: RAND Corporation, TR-557-AF, 2008.

6 Intermediate results for two platforms can be found in the appendix.

Figure S.1. Summary of Probability of Identification

		NIIRS ID Req.	1 RPA Base	1 RPA Gr-5	1 RPA Gr-4	1 RPA Gr-3	3 RPAs Base	3 RPAs Gr-5	3 RPAs Gr-4	3 RPAs Gr-3
Day	Clear	7.0	G	G	G	G	G	G	G	G
		8.0	Y	G	Y	O	G	G	G	G
	Fog	7.0	G	G	G	Y	G	G	G	G
		8.0	O	Y	O	B	G	G	G	Y
	Cloud	7.0	O	O	R	O	O	O	G	G
		8.0	R	O	R	O	O	O	G	G
Night	Clear	7.0	G	G	R	R	G	G	G	G
		8.0	G	G	B	B	G	G	Y	O
	Fog	7.0	G	G	R	B	G	G	G	O
		8.0	G	G	R	B	G	G	G	O
	Cloud	7.0	O	O	R	B	Y	Y	G	O
		8.0	R	O	R	B	O	Y	G	O

(Column header "Weather" spans the first two columns.)

Scale (%)	
G	90 – 100
Y	80 – 90
O	70 – 80
R	50 – 70
B	0 – 50

Figure S.2. Summary of Probability of Maintaining Track to the Kill Zone

		NIIRS ID Req.	1 RPA Base	1 RPA Gr-5	1 RPA Gr-4	1 RPA Gr-3	3 RPAs Base	3 RPAs Gr-5	3 RPAs Gr-4	3 RPAs Gr-3
Day	Clear	7.0	G	G	O	O	G	G	G	G
		8.0	Y	G	B	B	G	G	G	G
	Fog	7.0	G	G	R	B	G	G	G	G
		8.0	O	Y	B	B	G	G	G	Y
	Cloud	7.0	O	B	B	R	O	R	Y	G
		8.0	R	B	B	B	O	R	Y	G
Night	Clear	7.0	G	G	R	B	G	G	G	O
		8.0	G	G	B	B	G	G	G	O
	Fog	7.0	G	G	B	B	G	G	Y	R
		8.0	G	G	B	B	G	G	Y	R
	Cloud	7.0	O	R	B	B	O	O	G	Y
		8.0	R	R	B	B	O	R	G	Y

Scale (%)	
G	90 – 100
Y	80 – 90
O	70 – 80
R	50 – 70
B	0 – 50

Conclusions

From the analysis that underlies these summary charts, we arrived at four general findings.

First, *there is no silver bullet for RPA performance in the hunter-killer mission*. Even in this highly constrained example, no single RPA concept performed well on all measures under all environmental conditions.

Second, *numbers can compensate for capability*. In this scenario, two or three smaller RPAs with less-capable sensor packages were often able to equal or exceed the performance of the larger RPAs employed singly.

Third, *the MQ-9 holds up well against the other RPA design concepts we modeled in this scenario*. The MQ-9 was never dramatically outperformed and never fared worst on any measure. It compared favorably under most environmental conditions.

Finally, *improving MQ-9 sensor capabilities may be a cost-effective option*. Although we did not perform a cost-effectiveness analysis, upgrading the sensors on existing MQ-9 platforms, in particular their FMV sensor capabilities, would permit greater operational flexibility and would offer enhanced operational effectiveness for this type of hunter-killer scenario. Furthermore, if the discrete levels of magnification currently available on the Multispectral Targeting System, Model B (MTS-B) could be replaced with a continuous zoom feature, MTS-B could be used more effectively to enable the RPA pilot and sensor operator to balance competing mission objectives.

Acknowledgments

We would like to thank our sponsors, Randall Walden (SAF/AQI), Lt Gen Larry James (AF/A2), and Maj Gen Andersen (ACC/A8), for their guidance throughout this study. We owe a debt of gratitude to many other Air Force staff who helped us with this work as well, including Brian Bergdahl (SAF/AQIJ), Col James Geary (AF/A2CU), Col Robert Killefer III (AF/A2DS), Col James Beissner (ACC/A8Q), and many others.

Thanks also to Greg McNeil, Eric Frisco, and Taylor Mitchell of ExoAnalytic Solutions for their help in making better use of the SEAS modeling environment. Finally, we thank our RAND colleagues Rachel Costello and Joel Kvitky for their invaluable assistance with this study and Robert A. Guffey for his help in drafting the report.

Abbreviations

CEP	circular error probability
CONOPS	concept of operations
DoD	U.S. Department of Defense
ELINT	electronic intelligence
EO	electro-optical
ERP	effective radiated power
FMV	full-motion video
FOV	field of view
GIQE	general image quality equation
GMTI	ground moving target indicator
GSD	ground sample distance
ID	identification
IR	infrared
ISAR	inverse synthetic aperture radar
LOS	line-of-sight
MSL	mean sea level
MTI	moving target indication
MTS-B	Multispectral Targeting System (Model B)
NIIRS	National Imagery Interpretability Rating Scale
PED	processing, exploitation, and dissemination
Pk	probability of kill
RCS	radar cross section
ROE	rules of engagement
RPA	remotely piloted aircraft
SAR	synthetic aperture radar
SCOPEM	Systems and CONOPs Operational Effectiveness Model

SEAS	System Effectiveness Analysis Simulation
SIGINT	signals intelligence
V-NIIRS	video NIIRS
WAMI	wide-area motion imagery

1. Introduction

Background

Air Force remotely piloted aircraft (RPAs)—in particular, the medium-altitude, multirole platforms, the MQ-1 Predator and MQ-9 Reaper—have provided crucial support to counterinsurgency and counterterrorism operations over the past decade.[7] However, the last of the Predators has now rolled off the assembly line,[8] and Air Force orders for new Reapers have reached a steady state.[9] To meet future needs, the Air Force has now begun to assess concepts for a potential follow-on RPA system.[10]

The research presented in this report is part of a larger study that examined the effectiveness of several notional design concepts for RPAs. Here, we present in detail the analysis of a permissive hunter-killer mission.

In this report, we analyze the operational effectiveness of three RPA design concepts, plus the MQ-9 as a baseline, on a hunter-killer mission: to find and destroy a specific moving vehicle. All the findings in this report are based on the modeling results for a particular scenario (with variants) and should be understood within that context.

Study Approach

Figure 1.1 outlines the overall analytical approach. The heart of the analysis was performed using RAND's Systems and Concepts of Operations (CONOPS) Operational Effectiveness Model (SCOPEM),[11] an interlocking suite of sensor, environment, and platform modules built

---

[7] The nomenclature for these aircraft can be somewhat vexing, because the MQ-1 Predator has many offspring. The MQ-9 Reaper was originally conceived as an improved Predator and is still sometimes referred to as the "Predator B"—which is not to be confused with the MQ-1B, the designation for a newer, upgraded version of the original Predator. Similarly, General Atomics refers to its next-generation RPA system as the "Predator C" Avenger, which is not to be confused with the Army's MQ-1C Grey Eagle (formerly Sky Warrior), an even newer variant of the Predator. Finally, it is worth noting that the MQ-1 was formerly designated the RQ-1 prior to the addition of weapons in 2001. This older designation is still used on occasion to emphasize that a particular airframe carries no weapons.

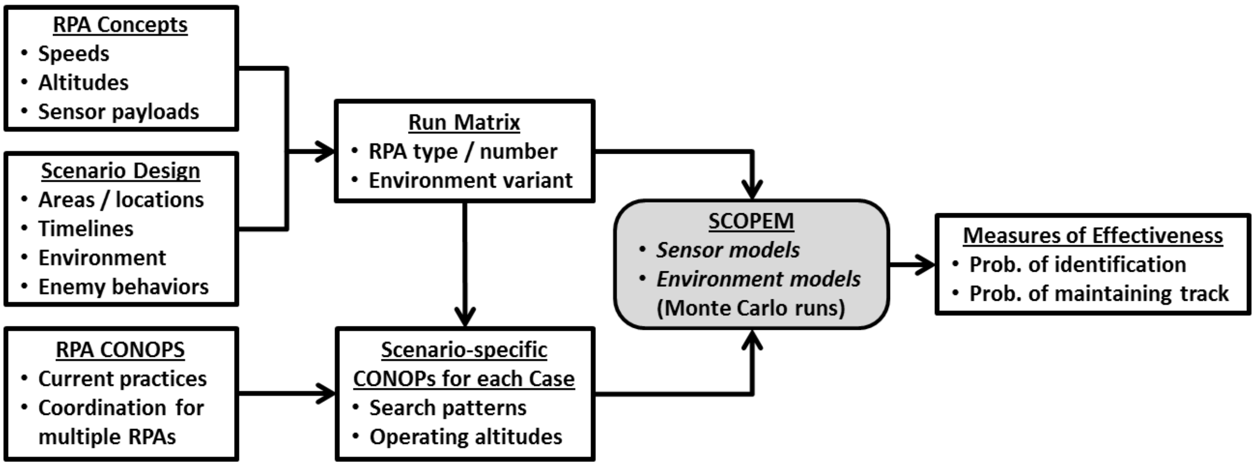
[8] 88th Air Base Wing Public Affairs, "Air Force Accepts Delivery of Final MQ-1 Predator," Wright-Patterson Air Force Base, Ohio, March 4, 2011.

[9] Recent planning calls for a fixed quantity of 48 aircraft per year for the next several years. See U.S. Department of Defense (DoD), Aircraft Procurement Plan Fiscal Years 2012–2041, Washington, D.C., A-A78844C, March 2011a, Chart 8.

[10] Dave Majumdar, "Air Force Orders Single Predator C Avenger," *Air Force Times*, December 13, 2011.

[11] Formerly known as the Collections Operations Model. See Lance Menthe and Jeffrey Sullivan, *A RAND Analysis Tool for Intelligence, Surveillance, and Reconnaissance: The Collections Operations Model*, Santa Monica, Calif.: RAND Corporation, TR-557-AF, 2008.

Figure 1.1. Diagram of Methodology



within the Air Force's agent-based System Effectiveness Analysis Simulation (SEAS) modeling environment. SEAS is part of the Air Force Standard Analysis Toolkit. Using this model, we performed a Monte Carlo analysis of each of the 144 variants of the hunter-killer scenario we considered.

Design Concepts Considered

The RPA design concepts we examined were developed as part of the larger study. The study overview document discusses these concepts and their development in more detail.

The concepts are meant to represent typical parameters for what the Air Force defines today as "Group 3," "Group 4," and "Group 5" classes of RPAs, with operational performance and sensor packages comparable to those of today's aircraft with similar size, weight, and power.[12] The designs are not radical but were selected in an attempt to analyze middle-of-the-road options with conservative assumptions about future capabilities. Thus, the RPA design concepts we assessed reflect what is currently practical rather than what may be possible in the future.

Table 1.1 summarizes the basic specifications of the design concepts and provides comparable data for the MQ-9.

---

[12] These groups are categorized roughly as follows. Group 3 is anywhere in the large range of 56–1320 lbs., less than 250 knots indicated airspeed, and an operating altitude below 18,000 ft. above mean sea level (MSL). Group 4 is anything greater than 1320 lbs. at any airspeed, with the same restriction on operating altitude as for Group 3. Group 5 is the same as Group 4 but with an operating altitude above 18,000 MSL (DoD, *Unmanned Systems Integrated Roadmap FY 2011–2036*, Washington, D.C., November 9, 2011b, p. 12, Figure 1). As is evident, these definitions are very broad. They span the space of possibilities, but only because they specify so little. Future research on more advanced RPA concepts would benefit from a richer nomenclature.

Table 1.1. RPA Design Concepts

Concept	Payload (lbs.)	Cruise Speed (knots)	Electro-Optical (EO) and Infrared (IR) Full-Motion Video (FMV) Sensor	GMTI and Synthetic Aperture Radar (SAR) Sensor
MQ-9 Reaper	3,850[a]	180[b]	MTS-B	Lynx
Group 5	4,000	360	MTS-B	Lynx
Group 4	535	125	Raven Eye II	—
Group 3[c]	35	70	Raven Eye I	—

[a] Includes 850 lbs. internal and 3,000 lbs. external payload capacity.
[b] The actual cruise speed varies. We selected this figure for consistency of analysis.
[c] This is the “light” version. A “heavy” version was included in other parts of the study, but was omitted from this analysis due to the similarity in performance and capabilities in this scenario.

We chose not to examine the smallest RPA concepts, i.e., Group 1 (micro- and mini-tactical) and Group 2 (small tactical) for this particular hunter-killer scenario. Despite their potential utility for many other missions, these smaller RPAs can carry only very light payloads and must fly at low altitudes, which would require a very different suite of sensors and CONOPS to be successful in this scenario. Also, as a practical matter, these concepts were not developed as part of the larger study. The employment possibilities and operational effectiveness of smaller RPAs in missions like this one merit further research.

Organization of This Report

Section 2 describes the modeling approach and the sensor and environmental modules within SCOPEM that are relevant to the analysis. Section 3 details the particular hunter-killer scenario we modeled. Section 4 presents the modeling results, and Section 5 summarizes the findings that were drawn from these results. Finally, the appendix contains a condensed version of the complete numerical modeling output.

2. Modeling Approach

Modeling Environment

The underlying modeling environment, SEAS, is a stochastic, programmable, multiagent simulation sponsored by the Air Force Space Command, Space and Missile Systems Center, Directorate of Development and Planning.[13] SEAS is part of the Air Force Standard Analysis Toolkit and the Air Force Space Command Modeling and Simulation Toolkit. SEAS has been in use in one form or another for over fifteen years. The latest stable release (March 2011) is version 3.9.[14] SEAS is written in C++ and runs on the Microsoft Windows platform.

SCOPEM is RAND's unique modular approach to scenario construction in SEAS, designed to add richness and to facilitate exploratory modeling of variations at the mission level. Figure 2.1 depicts the conceptual relationship between SCOPEM and SEAS to the extent that SCOPEM is a suite of models within the SEAS modeling environment. Note that, while SEAS provides the scaffolding, all the systems and their interactions belong to SCOPEM.[15]

An agent in SEAS can be programmed to do almost anything; however, the agent requires programming for almost everything it does.[16] The situation is analogous to working with Microsoft Excel, in that the environment can be used to do many calculations, but it loads as an empty sheet. Rather than generating specialized, one-off models for each scenario—the standard approach to SEAS model development—SCOPEM builds all scenarios from common pieces. Today, SCOPEM's library encompasses models of hundreds of sensors, weapons, and platforms. Figure 2.2 offers an example of the graphical output of SEAS.

---

[13] First created by the Aerospace Corporation, SEAS is now maintained and developed for the Air Force by ExoAnalytic Solutions.

[14] Because the latest version was released after this study was already well under way, however, the authors decided to continue work with the previous version rather than change horses in midstream. SEAS version 3.8h1 was used for this research.

[15] Although SEAS itself is written in C++, SCOPEM is written in the Tactical Programming Language, a custom language used to script agent behaviors within SEAS.

[16] What exactly constitutes a software "agent" is a controversy we do not engage here. For our purposes, we speak of an *agent* as that entity within SEAS that has its own perceptions and can be programmed to make decisions based on those perceptions.

Figure 2.1. SCOPEM is a Library of Interacting Models in the SEAS Modeling Environment

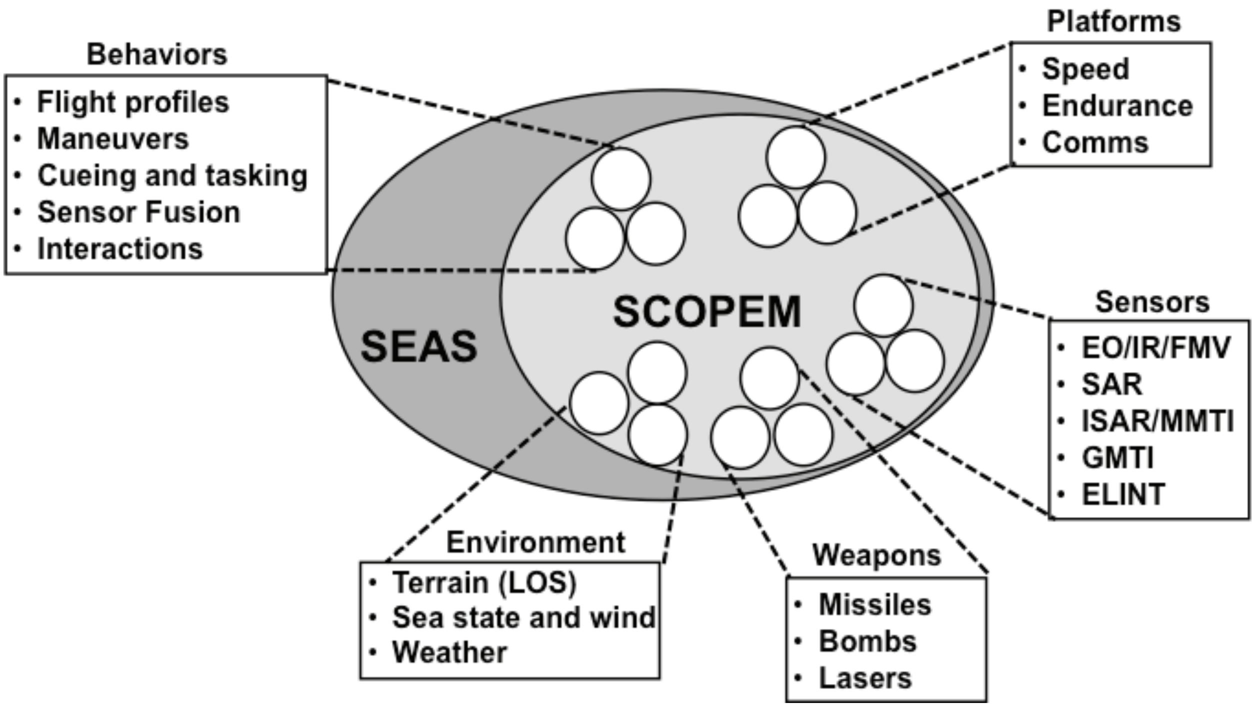
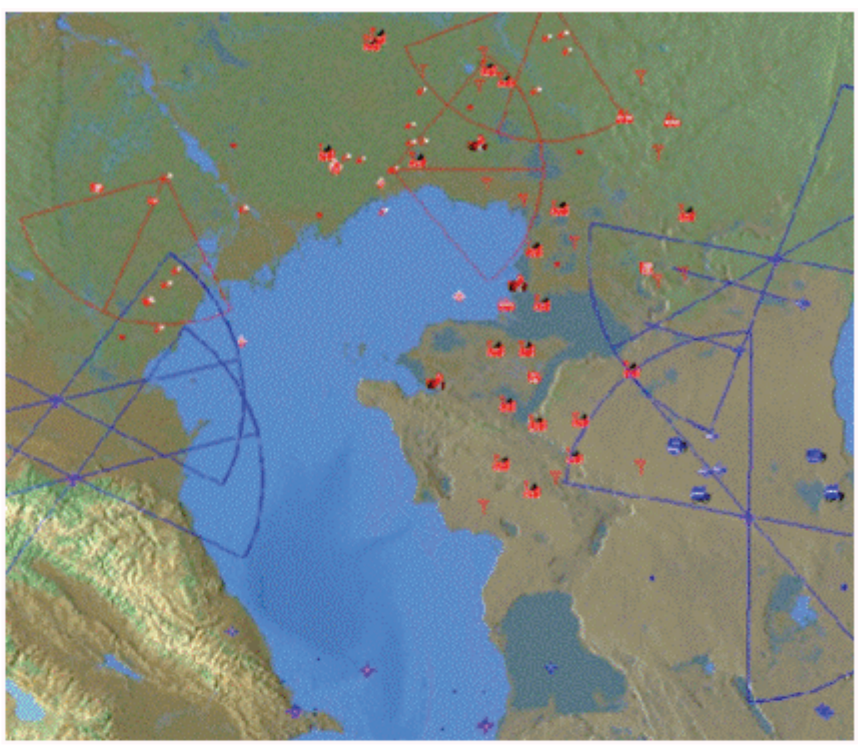
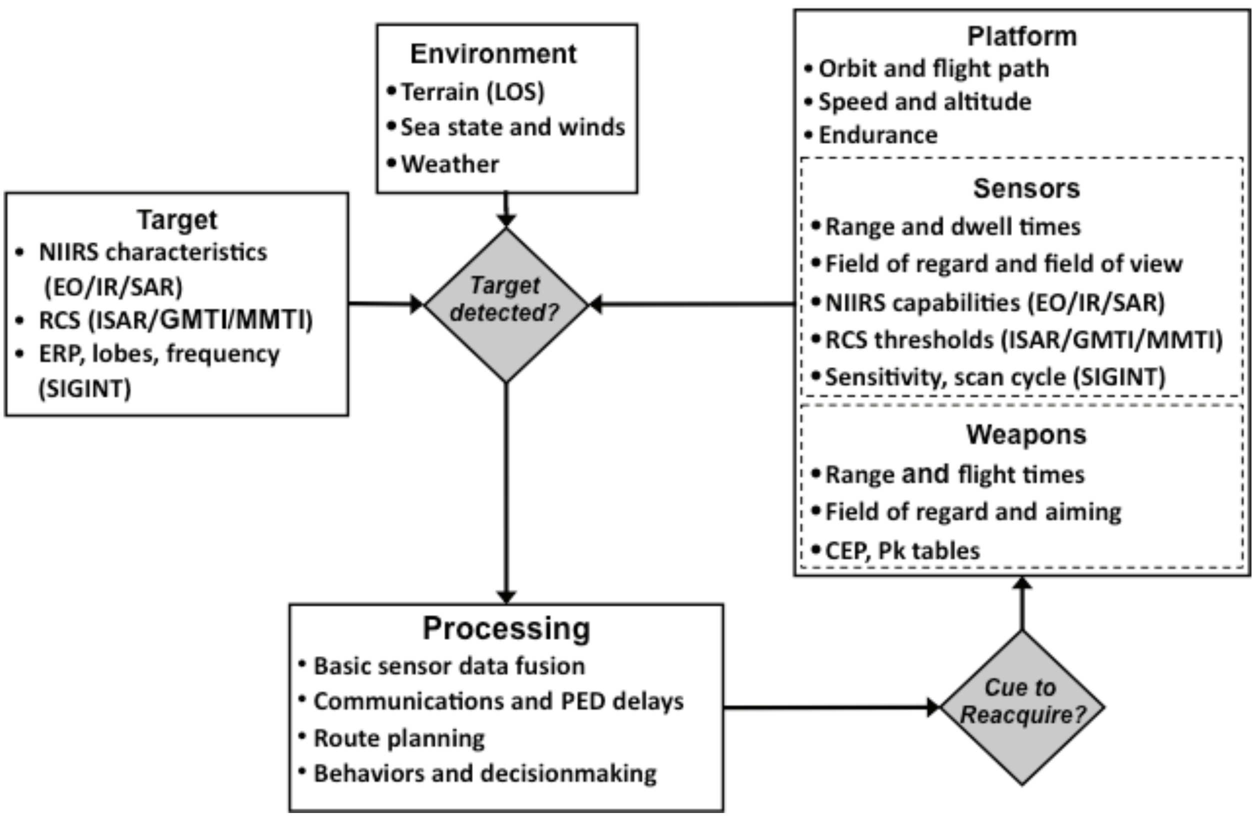


Figure 2.2. Example of the Graphical Output of SEAS Running SCOPEM



As a mission-level model, SCOPEM represents each platform, sensor, and weapon separately but does not simulate the finer details of these systems—e.g., aerodynamics and waveform propagation are not simulated explicitly. Instead, more-detailed models of these other phenomena are used to generate the necessary representations of sensor performance and environmental conditions in SCOPEM. These other models are documented elsewhere.[17] The interactions between these models, however, are within SCOPEM itself. Although these interactions can become quite complex, the core behavioral loop common to nearly all agents is the dynamic interaction between the sensor and target, as mediated by the environment. Figure 2.3 depicts this loop.

Figure 2.3. Overview of SCOPEM's Primary Loop



[17] Sherrill Lingel, Lance Menthe, Brien Alkire, John Gibson, Scott A. Grossman, Robert A. Guffey, Keith Henry, Lindsay D. Millard, Christopher A. Mouton, George Nacouzi, and Edward Wu, *Methodologies for Analyzing Remotely Piloted Aircraft in Future Roles and Missions*, Santa Monica, Calif.: RAND Corporation, DB-637-AF, 2012.

In the past, SCOPEM has been used to model a range of different operations, from maritime surveillance to nontraditional intelligence, surveillance, and reconnaissance, and different modules have been added with each study. In the subsequent sections, we describe the specific sensor and environment modules developed and used for the hunter-killer mission.

Although SCOPEM also contains weapon models, we chose not to model the entire "kill" portion of the scenario within this analytic framework. Some of the airframes considered are too small to carry both weapons and sensors, and CONOPS for calling in other aircraft would have been required for a fair comparison. Instead, we made the critical assumption that, if the remaining stringent conditions for a successful hunter-killer mission were met—if the target could be found, identified, tracked to a designated kill zone, and maintained continuously in track for a sufficiently long time—the RPA could either kill the target itself or, depending on the circumstances, call in another aircraft to do so. We did not model varying weapon performance.

Sensor Models

Three particular sensor modalities played a role in this study: motion imagery, specifically FMV; GMTI with an associated tracking system; and SAR. Each of these modalities has a different representation within SCOPEM. Here, we describe the key assumptions involved, those important to understanding and qualifying the results of the analysis of the hunter-killer mission. In all these models, we made the heroic assumption that the RPA had sufficient communications and processing, exploitation, and dissemination (PED) capacity. We did so to focus on sensor performance characteristics. In reality, PED constraints can be quite significant, and the issue merits further attention. In keeping with the assumption of an effectively permissive environment, we also did not consider such effects as jamming or the loss of Global Positioning System connectivity.

Full-Motion Video

Because FMV is the only sensor modality employed in this scenario capable of making a clear, positive identification of the target, the way in which FMV image quality is modeled can strongly affect the scenario outcome. Although alternatives to FMV certainly exist for this purpose, we chose to emphasize FMV because of the way it is treated in similar missions today. Note that the standard specifications for FMV sensors—resolution, focal length, etc.—are critical but are not in themselves sufficient to determine image quality, although they are certainly good indicators.[18] In SCOPEM we use a modified version of the general image quality equation

[18] Where possible, of course, we would always prefer to use actual performance data to characterize sensor capabilities, such as image quality; however, this was not (and rarely is) possible.

(GIQE) to estimate image quality based on these standard sensor specifications and sensor-target geometry.[19]

The GIQE is a regression-based predictor of image quality in terms of the National Imagery Interpretability Rating Scale (NIIRS), an empirical zero-to-ten scale that describes the types of exploitation tasks an image may be expected to support.[20] Working with trained imagery analysts, U.S. government agencies have developed tables that estimate the NIIRS levels required to detect, classify, or identify various objects within an image; we use these tables together with the GIQE to decide whether an image is of sufficient quality to identify the target.[21] The GIQE is an unbiased estimator of NIIRS, with a standard deviation of 0.3 levels.[22]

SCOPEM uses a simplified version of the GIQE for its calculations. The dominant parameter in the GIQE is the ground sample distance (GSD), a combination of angular resolution and sensor-target geometry (see Figure 2.4). The simplified equation implemented in SCOPEM replaces most other parameters (e.g., the relative edge response of various surfaces, which is very difficult to predict) with their average values, as determined from the initial sampling of images used to create the GIQE. To the extent that these parameters are not correlated with other aspects of the scenario, this simplification should not be expected to make a significant difference because the Monte Carlo nature of the simulation would ultimately average over these parameters anyway. However certain effects of the environment on image quality, such as line-of-sight (LOS) obstructions and atmospheric effects, are likely to be correlated. We model the impact of these environmental effects separately, as discussed in the next subsection.

Camouflage and concealment would also affect the ability to identify the target in an image. Because these cannot be treated effectively in a simple manner, our simulation is limited to the cases in which the target does not employ these techniques. Our assumptions are therefore optimistic in this regard.

All the FMV sensors modeled in this study are in fact suites of sensors with both EO (visible) and IR components. EO NIIRS and IR NIIRS are separate scales, and there are somewhat different versions of the GIQE for each. The EO and IR NIIRS scales are not technically identical in composition, meaning that an EO NIIRS of a certain level does not promise the same ability to detect, classify, and identify objects as an IR NIIRS of the same level; these differences are accounted for in the modeling.

---

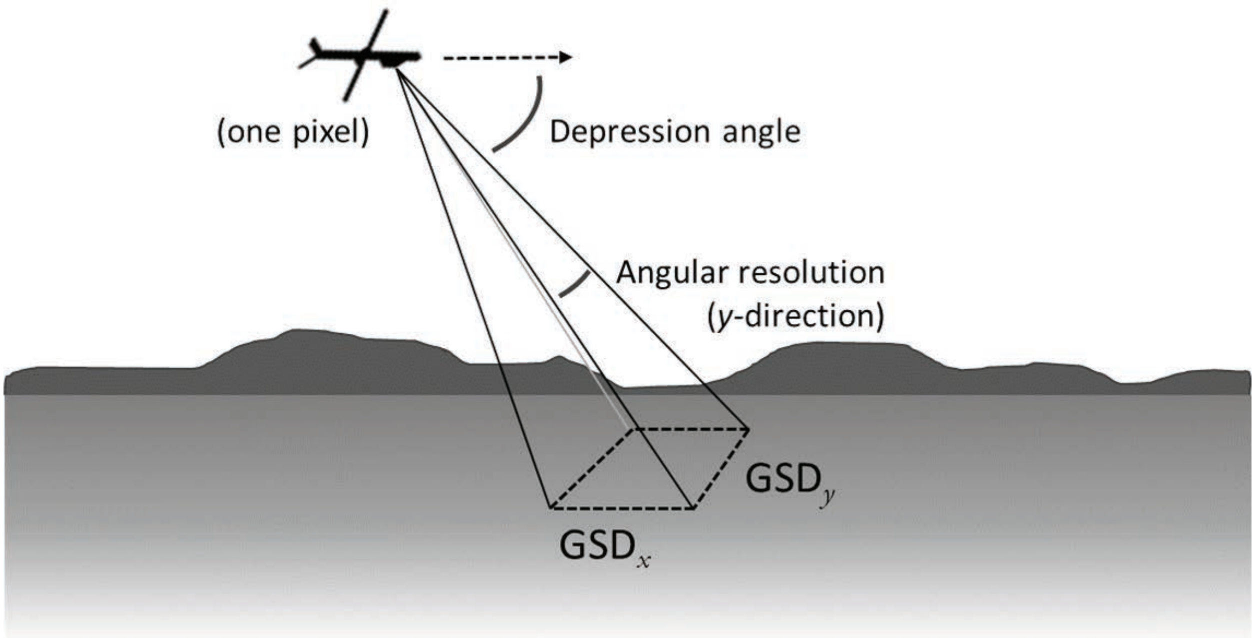
[19] Jon C. Leachtenauer, William Malia, John Irvine, Linda Colburn, and Nanette Salvaggio, "General Image-Quality Equation: GIQE," *Applied Optics*, Vol. 36, No. 32, November 10, 1997.

[20] John M. Irvine, Ana Ivelisse Aviles, David M. Cannon, Charles Fenimore, Donna S. Haverkamp, Steven A. Israel, Gary O'Brien, and John Roberts, "Developing an Interpretability Scale for Motion Imagery," Optical Engineering, Vol. 46, No. 11, p. 117401, November 2007.

[21] Imagery Resolution Assessments and Reporting Standards Committee, *Civil NIIRS Reference*, March 1996.

[22] As NIIRS is an integer scale, we treat the integers as thresholds. We explicitly model the 0.3 NIIRS variation within SCOPEM.

Figure 2.4. Ground Sample Distance



NOTE: The actual GSD used in the GIQE (and SCOPEM) is the geometric mean of the cross-range (GSDy) and downrange (GSDx) terms. If the image is skewed such that these directions are not orthogonal, the GSD must be further modified.

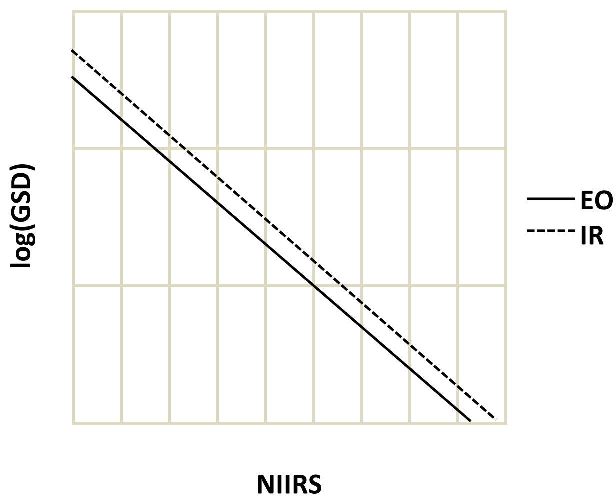
Figure 2.5 illuminates one curiosity of the GIQE worth noting. All other things being equal, the EO and IR versions of the GIQE would estimate the interpretability of an IR image to be better than that of the corresponding EO image with the same GSD. This apparent contradiction with experience is resolved by observing that all other things are usually not equal. In particular, the resolution of the IR sensor is usually poorer than that of the corresponding EO sensor in the same mode, which leads to a coarser GSD.

However, this does highlight a particular concern with the version of the GIQE implemented in SCOPEM. As mentioned above, we invoke a simplified version in which the values of most other parameters are replaced by their averages. This practice is more problematic for IR images, however, because some of the GIQE parameters, notably the contrast, vary considerably between night and day and on the ambient temperature of the background clutter. They may even vary across the image itself, making some features more difficult to discern than others. For this reason, the IR results reported here should be viewed more cautiously, as optimistic projections.

The perceptive reader will notice, however, that these two NIIRS scales refer to still imagery, not motion imagery. Although there are analogous video NIIRS (V-NIIRS) scales,[23] there is as yet no similarly accepted general motion image quality equation to estimate V-NIIRS for either EO or IR motion imagery. We therefore follow the standard practice of treating an FMV feed as

[23] Motion Imagery Standards Board, *Recommended Practice: Video-NIIRS*, MISB RP 0901, October 15, 2009.

Figure 2.5. EO NIIRS and IR NIIRS Versus GSD (simplified relationships)



a series of still images and approximating the V-NIIRS of the FMV feed as the NIIRS of a still image taken from that feed. Preliminary studies suggest that this procedure yields a conservative estimate, likely underestimating V-NIIRS about 0.3 levels, but we make no assumption in this regard.[24]

It should also be noted that tracking by FMV is an important exploitation task included on the V-NIIRS scale that has no analog in standard, still-imagery NIIRS. For the analyst to reliably and consistently distinguish the target vehicle from the other vehicles on the road using FMV, we assumed that the corresponding still images in the FMV feed had to be of sufficiently high resolution that the analyst could at least *classify* the target.[25] So, to keep track of the vehicle as it progressed, we did not require the image quality to be maintained at such a high level that the target could always be positively identified, but also we did not accept that an image in which the vehicle was merely a blob would be sufficient. Instead, we sought to split the difference. In the absence of a better analytic model for predicting V-NIIRS analogous to the GIQE, we did not feel justified in making any more-refined assumption. (Note, however, that the rules of engagement [ROE] we employed required the target to be successfully identified before the kill.)

Finally, in this analysis, we did not model wide-area motion imagery (WAMI) systems, such as Gorgon Stare. These systems pose significant challenges for exploitation that we were not prepared to consider in the overall study. This remains an important area for future work.

[24] Irvine et al., 2007.

[25] Classification is an intermediate degree of understanding, between detection and identification.

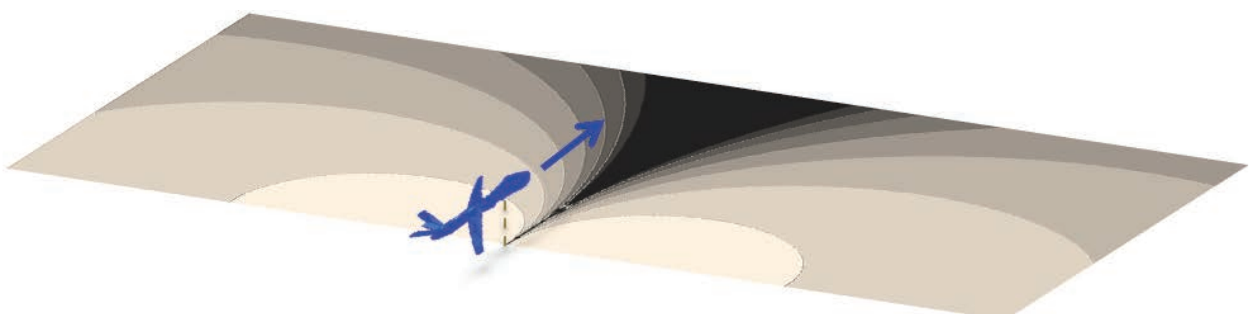
Synthetic Aperture Radar

Although less widely used than the corresponding EO and IR equations, a version of the GIQE has been adapted and related to SAR images, and there is a corresponding SAR NIIRS scale.[26] As with EO and IR, SCOPEM uses the GIQE along with standard SAR NIIRS tables to estimate which targets can be detected, classified, or identified in a given SAR image. (Note that we do not model tracking with SAR because the SAR systems in question cannot effectively image moving targets.[27])

At particularly low grazing angles, however (below 8 degrees), this method does not capure the degradation of SAR imaging well. As part of the preceding methodology development effort, the SAR model in SCOPEM was enhanced to employ a modified GSD that depends explicitly on the grazing angle.[28]

Unlike EO and IR imagery, SAR images cannot be modeled simply as snapshots—they must be built up over time as the platform carrying the SAR sensor flies to achieve an angular spread on the target.[29] The required angular spread is typically about 2 or 3 degrees of parallax, which typically requires 1 or 2 minutes of dwell time, depending on platform speed and sensor-target geometry. As Figure 2.6 illustrates, the dwell-time requirements mean that nearby targets off to

Figure 2.6. Notional Variation of SAR Dwell Time Required to Image Targets on the Ground



NOTE: Darker colors represent longer required dwell times.

---

[26] Ronald G. Driggers, James A. Ratches, Jon C. Leachtenauer, and Regina W. Kistner, "Synthetic Aperture Radar Target Acquisition Model Based on a National Imagery Interpretability Rating Scale to Probability of Discrimination Conversion," *Optical Engineering*, Vol. 42, No. 7, 2003.

[27] Technically, SAR can detect very slow-moving vehicles, but in our model, the target either stops or drives with the speed of traffic—the target vehicle does not creep along at one or two miles per hour.

[28] For a fuller discussion, see Lingel et al., 2012.

[29] Generally speaking, the target must be stationary during the collection process. Although the integration algorithms used to construct the SAR image could, in principle, compensate for known target motion, this is rarely implemented, in part because the relative motion of background with respect to the target would smear the rest of the image. Similarly, while SAR images can, in principle, be integrated over an arbitrary flight path, in practice, most algorithms require the collecting platform to fly in a straight line or a smooth arc.

the side can be rapidly collected in passing, but targets ahead require much more time to complete.[30]

Ground Moving Target Indicator

As part of the methodology development effort leading up to this report, we added more-complex models of GMTI detection and tracking to SCOPEM. Because SCOPEM does not represent explicit waveform propagation, it uses expressions at the macroscopic level, such as those derived from the radar range equation.[31] This is consistent with the approaches taken for the other sensor modalities.

In this model, the probability of detection by the GMTI radar depends on the signal-to-noise ratio and the clutter-to-noise ratio. The signal-to-noise ratio is estimated from the strength of the radar and the radar cross section (RCS) of the target; the clutter-to-noise ratio is a more-complicated calculation that depends on sensor-target geometry, the velocities and relative headings of the sensing platform and the target, and certain assumptions regarding the RCS of the background. A separate model must be calibrated to each specific GMTI sensor for implementation in SCOPEM. The probability of maintaining track for a given GMTI system is also determined offline and implemented in SCOPEM as a table of probability for a range of revisit intervals, target orientations, radar resolution, surrounding traffic density, and many of the parameters listed above.[32]

Environment Models

Environmental factors, such as terrain and weather, play a critical role in mediating sensor-target interactions. SCOPEM includes a variety of models for different environmental factors. In this subsection, we describe the particular models used in this scenario: LOS, fog, and cloud cover.

Line of Sight

When determining LOS, the most basic consideration is the overall geometry of the earth. SEAS natively models the earth's spherical geometry, as opposed to a flat-earth model—a distinction that is not always negligible. As depicted in exaggerated form in Figure 2.7, the sensor viewing angle ($\propto$) for an aircraft is always somewhat larger than the corresponding grazing angle (β), a distinction that a flat-earth model would ignore. This is implemented in all calculations involving sensor-target geometry within SCOPEM. It is mostly significant for SAR images taken at low grazing angles, where, as indicated above, the effect of low grazing angles

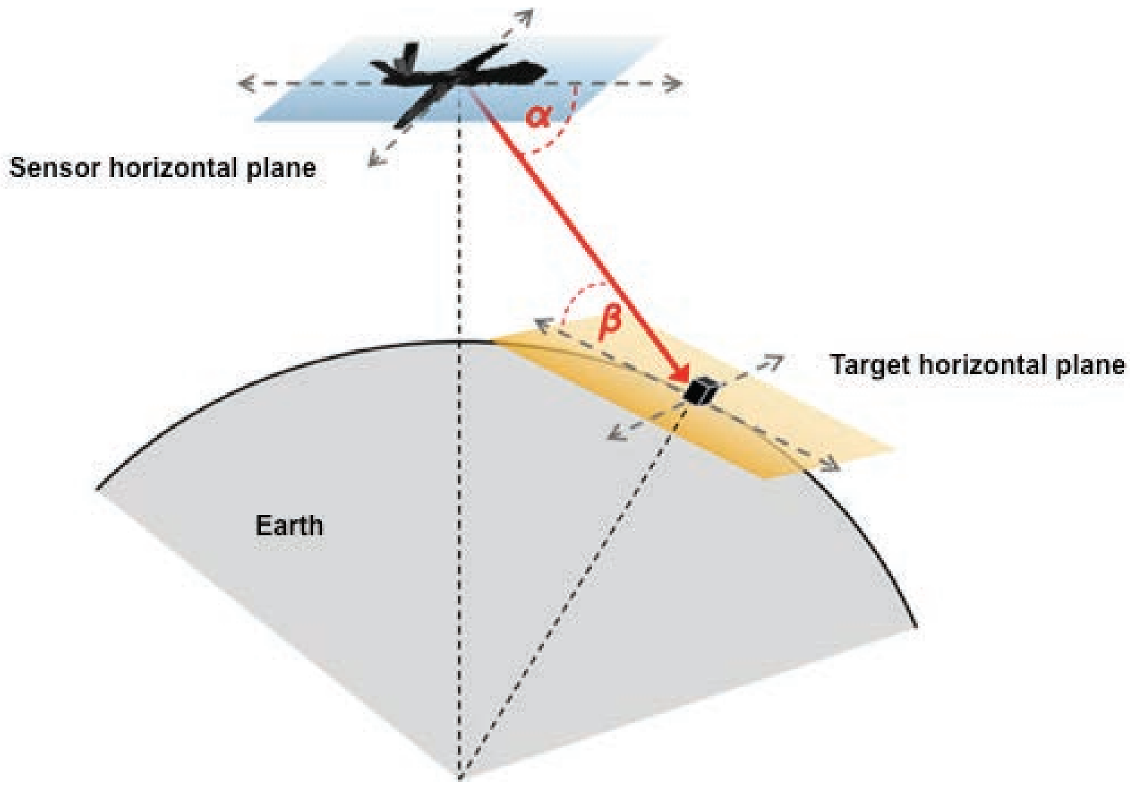
---

[30] If the dwell is interrupted, we assume no image is formed.

[31] Merrill I. Skolnik, *Radar Handbook*, 3rd ed., New York: McGraw-Hill, 2008.

[32] The details of these calculations are given in Lingel et al., 2012.

Figure 2.7. Spherical Geometry



must be modeled separately. Otherwise, for greater angles, at the altitudes relevant to this scenario (less than 50,000 ft.), the difference between spherical and flat-earth geometry is small.[33]

The primary determinant of LOS between the sensor and the target is their relative elevation and the surrounding landscape. Digital terrain elevation data are used to define contour lines at regular intervals in SCOPEM, which in turn are used to interpolate the altitudes of objects on the ground.[34] These contour lines also act as ridgelines that block LOS. We make the simplifying assumption in our model that LOS either is blocked or is not blocked—there is no partial obscuration—and we neglect other features of the terrain, such as unusually large rocks or trees. For the mountainous, desert area used for our scenario, these assumptions are adequate to represent coarse features of the landscape, but finer resolution is required for buildings in urban areas.

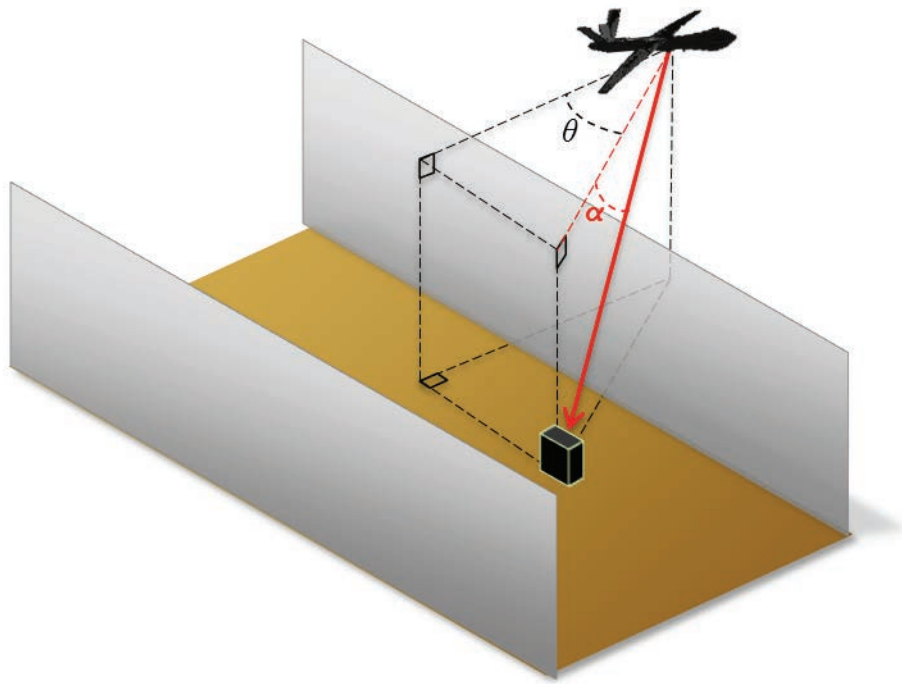
To represent the impact of "urban canyons" on the ability to track targets, SCOPEM overlays a separate LOS model for streets on top of the digital terrain elevation data contour lines described above. As shown in Figure 2.8, the relative height of the buildings along a road

---

[33] When calculating the GSD for NIIRS estimates, we take the image to lie in a horizontal plane centered on the target. For our purposes, the curvature of the earth within the image itself is always negligible.

[34] Typical spacing between contour lines is 50 m in elevation.

Figure 2.8. Urban Canyon Line-of-Sight Model in SCOPEM



compared to the width of the road (both of which may be set at will) determines the minimum viewing angle (∝), which varies with the obliquity of the aircraft's viewing angle relative to the road (θ). The specific minimum applicable to any given situation depends on the angle of the viewing platform relative to the road. SCOPEM allows multiple viewing angles at intersections. Roads are assumed to be two-lane roads, so the distance from the target to the side of the road is taken to be (on average) about one-quarter of the width of the road.

Fog

As discussed in the subsection on FMV modeling, some effects of atmospheric conditions on EO and IR image quality must be modeled separately. We use the Air Force Research Laboratory program MODTRAN to determine the approximate transmittance of EO and IR radiation through different atmospheres, as a function of range and viewing angles.[35]

To model the effects of fog or haze on image quality, the transmittance calculated in this manner is used to rescale the signal-to-noise ratio in the GIQE, one of the several parameters for which we previously used only the average value. The scaling factor is the ratio of the transmittance through fog to the transmittance on a clear day for the same range and viewing angle. (A ratio of zero would block all radiation; a ratio of one would yield no effect.) The result

[35] The particular instantiation of MODTRAN that RAND used for this effort is PCWinMod, Versions 4 and 5.

is a significant degradation of image quality for many EO systems, but less so for IR systems, because these wavelengths have greater ability to penetrate.[36]

Cloud Cover

SCOPEM implements a simplistic model of cloud cover designed to capture one particular effect: restricted LOS to ground targets when flying above the cloud ceiling. As before, we assume LOS is either completely clear or totally blocked at any given moment (i.e., the clouds are completely opaque) although the cloud cover above any given point will change over time. We model a single layer of clouds only: There is little advantage to modeling additional layers when using this simple of a representation.

To model the cloud layer, we look to Air Force Combat Climatology Center data to estimate the typical percentage of cloud coverage in a given region during a given season—and, where available, the average spatial and temporal coherence of that cloud cover. We divide the sky into a grid and populate each square as either clear or obscure, based on the typical percentage of cloud cover.[37] The spatial coherence is used to determine the spacing of the grid; the temporal coherence is used to determine how often the grid must be refreshed.

Note that, while we use a random draw to determine which squares are obscured, each square remains either clear or obscured until redrawn. We do not make a separate random draw for each viewing attempt because that would unrealistically allow a sensor to penetrate a patch of cloud merely by looking repeatedly. It also assures that all sensors in the region face the same pattern of obscuration. An aircraft can, however, see under a patch of cloud by obtaining a favorable viewing angle through a nearby hole.

Note that we do not model the effects of cloud cover on radar and do not model the effects of rainfall. (“Rain fading” is known to affect radar returns.[38]) We consider only partly cloudy weather without rain or other precipitation. Overcast skies would make the mission as defined here impossible for platforms flying above the cloud ceiling because the target could not be imaged with the quality necessary to identify it, while any significant precipitation would hamper operations beneath. A more-sophisticated model of RPA operations would be required to model the hunter-killer mission under such conditions.

---

[36] We considered transmittance effects for medium-wavelength IR radiation (approximately 3 to 8 μm).

[37] We use latitude and longitude to define the grid, which is therefore not strictly square, but narrower at higher latitudes. For the size of region modeled here, this variation is negligible.

[38] Skolnik, 2008.

3. The Hunter-Killer Mission

Introduction

The hunter-killer mission is understood best not as a specific mission but as a class of missions in which aircraft hunt for and ultimately kill a specific individual target on the ground. One or more aircraft may participate in the search; the search area may be large or small; the target may be mobile or stationary or may exhibit more-complex behaviors; the ROE may be loose or restrictive; and the environmental conditions can vary greatly.

The class of missions is too broad for us to explore fully. Instead, we selected one particular scenario so that we could explore its variants. We have chosen to examine a specific target in a specific geographical area while varying the number and type of aircraft, the ROE, and the environmental conditions. These choices allow us to explore certain basic considerations for RPA design concretely, but the analysis is far from exhaustive. Other scenarios would illuminate other trade-offs.

We selected the particular scenario that we did to draw out the differences in mission effectiveness between the particular RPA concepts we studied. It would not have been difficult to select a scenario in which all the RPA concepts we considered always succeeded or in which they never succeeded—but doing so would not have illuminated the trade-offs among them. We adjusted the CONOPS for each RPA concept to represent, as best we could, its intelligent employment in the hunter-killer mission.

Although the scenario we modeled is representative of many hunter-killer missions as they are executed today, it is not representative of others. It also relies on several crucial assumptions. Most important, the threat environment we modeled is permissive, meaning that there is negligible threat to the aircraft. This permits the use of CONOPS untempered by survivability concerns.

In the particular scenario we considered, the initial cue for the target vehicle is urgent but imprecise, allowing only that the enemy is expected to emerge from hiding somewhere in a 5 nmi^2 area within 15 minutes. The target's ultimate destination is believed to be outside of this area but is otherwise unknown. Finding the target vehicle before it leaves the area therefore necessitates a rapid, brute-force search.

Because the area is not especially large, the search is not difficult, but environmental factors complicate it. The cued area is an urban environment, which constrains LOS to steep viewing angles. Moreover, in many of the variants we considered, the RPA sensor operator is forced to contend with other effects detrimental to establishing and maintaining LOS, including fog and clouds. The parameters of the initial cue, as described above, were selected to highlight how these environmental conditions affect operational effectiveness.

The ROE and CONOPS we selected are also fairly restrictive. They require that the target be positively identified with FMV and that the RPA sensor operator keep the target in view with FMV whenever weather conditions permit. This places a high burden on the required resolution of the imagery, which must yield an estimated NIIRS quality level of 7.0 or 8.0.[39] (Both cases are modeled.) While reflective of current practice, these requirements effectively relegate GMTI to a lesser role than it could otherwise play. These requirements also preclude the RPA from flying at higher altitudes, which in turn reduces the effective ground coverage area that the RPA sensor operator can achieve. The ROE therefore force the RPA pilot to choose a flight profile that balances the competing demands for high resolution and greater ground coverage area.

We made several simplifying operating assumptions as well. We did not consider the possibility of communications jamming or loss of Global Positioning System connectivity, either of which could be potentially devastating. We assumed that each RPA had sufficient communications capacity and PED resources to fulfill its mission—a necessary but admittedly heroic assumption mandated largely by certain technical limitations. Finally, while the enemy is allowed some awareness that it is in danger of being watched, we assumed that it could neither see nor hear the RPA. The target vehicle also does not employ camouflage, concealment, or any of the other clever ruses that have at times been observed in the field: The only adaptive enemy behavior is to come to a halt from time to time, in an attempt to confuse possible GMTI tracking.

These choices and assumptions enabled us to avoid certain issues so that we could focus instead on the broader trade-offs between platform size and platform number; differing sensor performance; and the complicating effects of darkness, fog, and cloud cover. However, they also inherently limit the applicability of our findings on those trade-offs. Nevertheless, we believe that our analysis illuminates some important basic considerations in RPA design choices. It also demonstrates a successful analytical methodology that may be expanded to address more-challenging scenarios.

Sensor Capabilities

The sensor capabilities we considered drive the particular CONOPS for each RPA design concept to a considerable degree. Four sensors play a role in this analysis: the Multispectral Targeting System, Model B (MTS-B); Raven Eye I; Raven Eye II; and Lynx. The first three are FMV sensors, with both EO and IR collection capabilities. Lynx is a radar system with SAR and GMTI. The capabilities of these sensors are described here.

Multispectral Targeting System, Model B

The MTS-B has EO (daytime color) and IR (day-and-night monochrome) FMV capabilities. Each of these has several fixed modes of magnification or field of view (FOV), as given in

[39] For a description of the NIIRS scale, see Leachtenauer et al., 1997.

Table 3.1. For our purposes, we have grayed out the "Ultranarrow" mode because it is an electronic zoom of the "Narrow" mode, rather than a higher sensor resolution. All modes render FMV in 480×640 pixels, and the corresponding FOVs are always in that same 3:4 proportion.

The field of regard for MTS-B effectively extends 360 degrees in azimuth and down to 90 degrees in elevation (straight down), but in practice, such viewing angles are discouraged because they increase likelihood of losing the target. The short but nonnegligible latency inherent in controlling the RPA remotely implies that the sensor operator should "lead" the target it is attempting to track, which is more difficult in such cases. Note that the MTS-B does not have continuous zoom capabilities but allows only discrete modes, as shown in Table 3.1.

Raven Eye I

Raven Eye I is a lighter sensor package, with less resolution in its modes. The specifications of the various modes are given in Table 3.2. Note that the EO system (color television) has continuous zoom between the limits given, while the IR mode has fixed levels of magnification. The ability to zoom continuously in the EO mode allows the platform to sit in a "sweet spot" for the hunter-killer mission in nearly all cases, something not always possible for other sensors. The field of regard is, for our purposes, not limited.

Table 3.1. MTS-B Modes, Field of View, and Pixels

Mode	EO (degrees)	IR (degrees)
Ultrawide	34 × 45	34 × 45
Wide	17 × 22	17 × 22
Medium	5.7 × 7.6	5.7 × 7.6
Narrow-Medium	0.96 × 1.3	2.8 × 3.7
Narrow	0.16 × 0.22	0.47 × 0.63
Ultranarrow	0.08 × 0.11	0.23 × 0.31

SOURCE: Bart E. Bennett, Joel Kvitky, Daniel M. Norton, and Michael Nixon, *MQ-1 Predator and MQ-9 Reaper Air-to-Ground Sensor Capabilities*, Santa Monica, Calif.: RAND Corporation, TR-1174-AF, 2013, Not available to the general public, Table 8.
NOTE: Dimensions have been rounded to two significant figures.

Table 3.2. Raven Eye I Capabilities

Mode	EO (480 × 640) (degrees)	IR (320 × 240) (degrees)
Maximum (wide)	20.25 × 27.0 ↓ 0.64 × 0.85	16 × 22
Medium		5.2 × 6.9
Minimum (narrow)		1.3 × 1.7

Raven Eye II

Raven Eye II is similar to Raven Eye I, except that it has smaller FOVs and correspondingly higher resolution (Table 3.3). It is also three times heavier (110 lbs. versus 35 lbs.) because of its larger aperture.[40] Both aspects play a role in the hunter-killer mission we simulated. With Raven Eye II, and RPA can achieve the required NIIRS at a higher altitude, but the search area it can cover is likely smaller. As with Raven Eye I, the field of regard is effectively not limited.

Table 3.3. Raven Eye II Capabilities

Mode	EO (480 × 640) (degrees)	IR (256 × 256) (degrees)
Maximum (wide)	10.2 × 13.6 ↓ 0.3 × 0.4	13.5 × 13.5
Medium		2.9 × 2.9
Minimum (narrow)		0.73 × 0.73

Lynx

Lynx provides both SAR and GMTI capabilities.[41] This is the system on the Reaper today, although, in practice, the SAR mode is used infrequently, and its GMTI capabilities are currently exploited very little if at all. The Lynx SAR mode has 270 degrees azimuthal coverage; the rear quarter is not in the field of regard. The Lynx GMTI mode is more limited, with only 90 degrees azimuthal coverage—only the front quarter. Both modes are restricted in field of regard to viewing angles lower 60 degrees (the nadir is not visible). These limitations are important because they can interfere with the ability to track or image the target under some situations. Although the Lynx SAR has several spot-mode resolutions, we assume the highest resolution is used for imaging because this is necessary to obtain a suitable image for this mission.

---

[40] Northrop Grumman Corporation, “Raven Eye I: Unmanned Multimission Stabilized Payload,” factsheet, Falls Church, Va. DS-295-BAS-0803, undated a; Northrop Grumman Corporation, “Raven Eye II: Unmanned Multi-mission Stabilized Payload,” factsheet, Falls Church, Va. DS-296-BAS-0803, undated b.

[41] We simulated AN/APY-8, Lynx Block 20.

Specific Scenario

In our scenario, prior intelligence has indicated that the target is likely to emerge from hiding somewhere within an urban area of approximately 5.0 nmi^2 (approximately 17 km^2) within a particular window of time (about 15 min.). We made the simplifying assumption that the time window indicated by the cue is sufficiently circumscribed and the warning sufficiently advanced that the RPA may arrive on station prior to the window and may remain on station throughout its duration.[42] As we framed the problem, increased range and endurance would permit the RPA to prosecute effectively *a larger set* of the hunter-killer class of missions (e.g., longer time windows, or a farther distance from the base) than RPAs of lesser range and endurance, but these attributes would not affect operational effectiveness once on station.[43] This choice levels the playing field somewhat between the smaller and larger platforms for the purposes of comparison in this scenario. Relaxing this assumption would make the smaller RPAs less viable to the mission as a whole.

We used a small urban area near Afghanistan for scaling the landscape, the size of the city, and some of the road structure and as a reference point for typical weather conditions (see later discussion of flight profiles.) The urban area is not especially dense but is characterized by roads that are somewhat narrower than the heights of the buildings, creating an "urban canyon" effect. In the narrowest of these canyons, depending on the direction of the aircraft relative to the roads, the minimum required grazing angle could be as high as 63 degrees; shallower angles could leave portions of the road obscured.[44] In most cases, however, the minimum viewing angle was less restrictive.

Once on station, the RPA conducts a raster search for the target using FMV. (In a raster search, the sensor sweeps out a pattern back and forth in alternating rows, as a farmer might plow a field.) As will be discussed in the next subsection, the exact parameters of this raster search will vary based on environment, weather, and platform capabilities. The general scheme, however, is always the same: FMV sensors collect in a wide mode to detect vehicles and occasionally zoom in to a narrow mode to attempt to identify them.

An important alternative CONOPS that we did not explore would have been to use GMTI to cue the narrow identification mode of the FMV sensor. There are many variants of the hunter-killer scenario in which this CONOPS is likely preferable to a raster search, such as those that afford a better initial cue or a longer timeline. The particular scenario we chose, however, was not favorable to demonstrate this CONOPS. Because the ROE demanded positive identification

---

[42] Relaxing this requirement would reduce all measures by whatever fraction of the time window was missed.

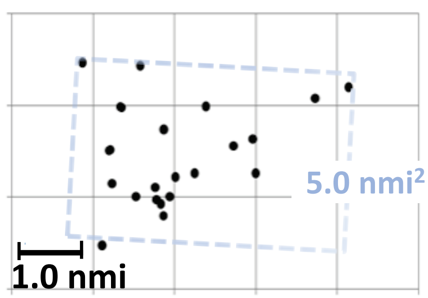
[43] Increased speed can improve operational effectiveness when on station, however, and this emerges from the subsequent analysis.

[44] We use *grazing angle* to mean the angle between the sensor-target line and the horizontal plane of the target and *viewing angle* to mean the angle between the sensor-target line and the horizontal plane of the sensor. As indicated earlier, these differ in more-realistic spherical geometry.

by FMV, because the NIIRS requirements for that identification were fairly strict, and because the vehicle emerged within an urban canyon that impaired LOS, the RPA was forced to fly closer to the ground and had more limited viewing angles than it otherwise would have enjoyed—all of which contributed to a significantly reduced effective ground coverage area. For this reason, the RPA sensor operator would only have been able to take very limited advantage of the wider field of regard that GMTI could provide.[45] Thus, we did not use GMTI to its fullest possible advantage in this analysis: We left it in a supporting role to FMV. Although this does, however unfortunately, reflect how the Reaper is most commonly employed today in similar hunter-killer missions—a fact which we intentionally captured—it does not accurately reflect the full potential of GMTI to contribute to this type mission, especially as part of a more-advanced future RPA concept. This is an area of research that should be further explored.

In this scenario, the target rides in a ground vehicle, either a small or large passenger truck.[46] At some random time, the vehicle will indeed emerge from a random hiding place and head to one of several possible destinations in a more rural area.[47] (We do not allow the RPA to know in advance where the target is ultimately headed.). The possible starting locations are shown in Figure 3.1.[48] The target will stop at irregular intervals in an attempt to elude pursuit, but otherwise moves with the speed of traffic on the road and employs neither camouflage nor concealment techniques. We assume there is one enemy vehicle only.

Figure 3.1. Initial Possible Starting Locations



---

[45] Attempting to identify all the targets in significantly a larger field of regard would also have required us to revisit our heroic assumption of sufficient PED.

[46] Modeled as approximately a 3 m^2 radar cross section.

[47] For simplicity, we assumed that the entire time window is either daylight or nighttime. This allowed us to distinguish more clearly the effects of EO versus IR sensors.

[48] For each Monte Carlo run, the starting and destination points are randomized; however, for any given pair of points, the vehicle will always follow the same route from one to the other.

If and when the RPA or RPAs locate the target, they will attempt to track it through the urban canyon to a suitable location outside the city, typically 5 to 10 nmi away (depending on the final destination), where the ROE permit attempting to kill the target.[49] Where available, onboard GMTI will be used to track vehicles, and SAR may also be used if the vehicle stops and weather conditions make FMV ineffective. If the RPA loses track of the vehicle, it will attempt to reacquire the track. (We assume it must also reidentify the vehicle in that case.) A representative screenshot of the graphical output of SEAS running a hunter-killer scenario is shown in Figure 3.2.

For multiple RPAs, tracking is cooperative: Each RPA's target sightings are sent to the others. Although these sightings are fused locally within each platform, so that there may be very minor differences, all RPAs have nearly the same operational picture in practice. We assumed that the target sightings shared in this manner are 100 percent correlated, meaning that all the RPAs are indeed attempting to track the same vehicle at the same time. Jamming and other potential communications difficulties are not considered. The tracking time required depended on the specific circumstances of when and where the target was identified and which destination it was headed toward, but typically the target needed to be tracked for about 15–20 minutes to reach the kill zone. Ambient traffic was not explicitly modeled.

Figure 3.2. Representative SEAS/SCOPEM Screen Shot

[49] The initial search area is sufficiently constrained that, in effect, target must be detected and identified within the urban canyon.

Flight Profiles

Choosing the right flight profile for each RPA concept is crucial to success in the hunter-killer scenario we modeled. Within the context of the FMV raster search in particular, we tuned the flight profiles separately for each RPA concept, sensor package, and weather condition to achieve the best mission outcomes under the circumstances. In a handful of cases, the flight profile changes partway through the mission, usually shifting to a higher altitude once the target has been identified and the task switches from searching to following. Although changing the search pattern in this manner could make certain types of comparison more difficult, this form of (limited) optimization reflects more accurately how an RPA pilot would actually conduct this kind of mission. Therefore, we believe this gives us better insight into the operational effectiveness achievable under the given conditions with these RPA concepts.

The key to determining the flight profile in most cases was selecting the initial flight altitude. To find and detect the target, the sensor operator uses a wider FMV mode, with lower resolution; identifying the target requires a narrower FMV mode with higher resolution. Ideally, the RPA would fly as high as possible to cover as much area as possible at one time (and possibly improve survivability as well) and still be able to perform both the detection and identification objectives, but there is an inherent tension between the two objectives. It was something of a surprise that the most stringent NIIRS requirement, positive identification of the target, was not always the limiting factor in operational effectiveness. This is because the FMV modes typically did not have continuous zoom but allowed only fixed levels of magnification. Thus, for example, in some cases it proved advantageous to fly at a somewhat lower altitude to take advantage of the wider FOV for detection that would otherwise be unable to provide the necessary image quality.

Because the NIIRS requirements we imposed on the mission were central to the mission design and outcome, we modeled two different cases. In the first case, we required NIIRS 8.0 for identification for both EO and IR sensors and NIIRS 4.0 for detection. In the second case, we considered alternative requirements of NIIRS 7.0 for identification, NIIRS 3.0 for detection by EO, and NIIRS 4.0 for detection by IR.[50] (Henceforth, we will use "NIIRS 8.0" and "NIIRS 7.0" as shorthand for these two sets of requirements, respectively.) In both cases, we used NIIRS 6.0 as the threshold for the RPA sensor operator being able to distinguish the vehicle reliably from nearby confusers for the purpose of following it with FMV.[51] For SAR, we set a requirement of NIIRS 3.0 for detection but set no requirement for identification, assuming that SAR alone would be incapable of satisfying the ROE for killing the target under these conditions. In all cases, EO sensors were used in daytime, IR sensors at night.

---

[50] These are reasonable values for vehicles and trucks. (For example, see Leachtenauer, 1997.) Given the primacy of FMV in this scenario, they may be considered the defining characteristics of these targets in our modeling, for all intents and purposes.

[51] NIIRS 6.0 was specified as the requirement for classification, although it played little role in the analysis.

We determined that, to be most effective, the smaller RPA concepts, carrying only Raven Eye I or Raven Eye II, needed to fly below the cloud ceiling. The larger RPA concepts, carrying the MTS-B/Lynx combination, however, were more effective flying above the cloud ceiling because the GMTI radar could often maintain track when the vehicle went behind a cloud. This determination does depend on the nature of the cloud cover, however. In our scenario, the cloud ceiling was taken to be 3,000 ft., with 40 percent cloud cover, consistent with the geographic area.

Table 3.4 summarizes the final altitudes for the model. The cloud cover parameters are as described above. For the case of fog, the transmittance of fog we modeled for visible (EO) wavelengths was taken to be approximately 0.125, and the transmittance for IR wavelengths was 0.75. (However note that these transmittances varied dramatically depending on viewing angle, ranging from 0.05 to over 0.90 depending on the circumstances. These figures are for the default 45-degree viewing angle we took for FMV detection and tracking during the raster search. See earlier discussion on fog for explanation of transmittance.)

It is also worth observing that the MTS-B, which offers only discrete viewing modes, did not always permit flight profiles that hit the "sweet spot" as well as the Raven Eye I and II, which offer continuous zoom capability. This capability allows the RPA sensor operator to balance the competing demands for higher resolution and greater ground coverage at will.

For multiple platforms, we were careful to stagger the timing to take maximum advantage of the search pattern. Once the vehicle was identified, the RPAs circled around the vehicle to keep it in view as they tracked it. The size of the circle was adjusted to keep the average viewing angle at approximately 45 degrees. Multiple platforms followed the same circle but staggered their angular spacing to take advantage of different simultaneous vantage points—this permitted them to keep the vehicle in view better in the urban canyon. For three vehicles, we chose even angular spacing (120-degree separation). For two vehicles, however, we chose uneven angular spacing

Table 3.4. Altitudes (ft. above ground level)

		NIIRS 7.0			NIIRS 8.0		
Sensors	**Time**	**Clear**	**Fog**	**Cloud**	**Clear**	**Fog**	**Cloud**
MTS-B / Lynx	Day	16,000	11,400	16,000	8,000	5,700	8,000
	Night	11,300	11,100	11,300	8,550	8,400	8,550
Raven Eye I	Day	8,900	6,350	3,000	4,500	3,200	3,000
	Night	1,975	1,950	1,975	1,550	1,500	1,550
Raven Eye II	Day	19,000	13,500	3,000	9,500	6,750	3,000
	Night	2,550	2,500	2,550	2,550	2,500	2,550

NOTES: Blue cells indicate that the resolution or FOV of the detection mode was the limiting factor. Yellow cells indicate that the resolution of the identification mode was the limiting factor. Gray cells indicate that cloud ceiling was the limiting factor.

(120 degrees and 240 degrees). Even spacing (180-degree separation) would place the RPAs on exact opposite sides of the circle, which proved suboptimal because they were both vulnerable to losing the target in the urban canyon at the same time.

Killing the Target

As mentioned earlier, we did not simulate weapons within SCOPEM. In our model, if the target could be successfully found, identified, tracked to a designated kill zone, and maintained continuously in track long enough, then the target could be killed. For our purposes, the key question is how much time is "long enough" to complete the strike. This depends on the CONOPS for killing the target, which in turn depends on whether any of the RPAs prosecuting the mission are carrying weapons or need to call in another aircraft to do so. It also depends on the command and control process that leads up to the decision to confirm the strike. In all cases, we relied on the assumption that the RPA(s) can communicate effectively with the combined air operations center during the "kill" portion of the hunter-killer mission. We looked at the two CONOPS described next.

Case 1: RPA Strike

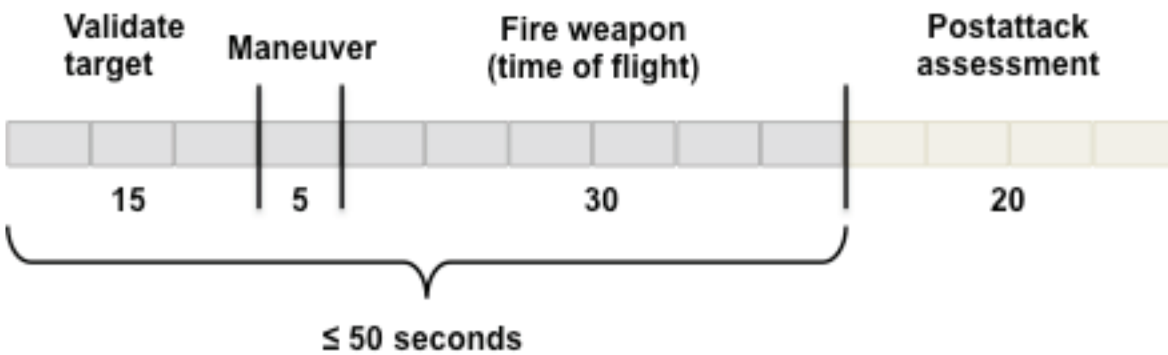
The most straightforward case is simply for the RPAs that hunt the target to kill it as well. This is usually how the hunter-killer mission is envisioned. This may not be possible for smaller RPAs concepts, but for the larger ones, like the MQ-9, it certainly is. In this case, the time lines are short. Once the target has been validated, meaning that the ROE are satisfied, the RPA maneuvers to employ weapons and then fires.[52] (Afterward, it presumably performs a postattack assessment.) Elapsed time from track to kill is 50 seconds or less. Depending on the weapon used, it may be necessary for the RPA to remain in visual contact with the target throughout the entire process. The situation is shown in Figure 3.3.

As indicated earlier, to reach the kill zone, the time for which the target had to be tracked varied considerably, but 15 to 20 min. was typical (and, within the model, the RPA usually retained track on the target for considerably longer than this). Given the somewhat arbitrary nature of the location of the "kill zone" and the "end" of the scenario and given the very short time line required for the strike itself, if the RPA was able to maintain track all the way to the "end" of the scenario, we assumed it had sufficient time to complete the firing process.

---

[52] We assume the RPA pilot has "on scene" commander authority to engage targets that meet the commander's guidance and ROE restrictions.

Figure 3.3. Single RPA Strike, Firing Timeline (times in seconds)



Case 2: Call for Fires

A more-challenging case involves the situation in which the RPA does not have the necessary weaponry to complete the strike. This may be because, as for Group 3 (and possibly Group 4), the airframe is too small or too underpowered to carry weapons in addition to the (large) sensor package. It may also be that there are different versions of the RPA—some with only sensors, some with only weapons—and a weaponized version must be pulled away from another task to complete the kill. This case is only applicable when basing is available and relatively close and when the United States has good access to the airspace for its strike aircraft.

In this situation, all the times described in the previous case also apply, plus an additional 5 sec. must be taken to transfer (digitally) the target geolocation data to the strike platform. (Unlike in Case 1, it was not previously tracking the target.) Of course, adding a few more seconds makes no difference in our model. The real challenge in terms of time comes from two sources: the command and control processes necessary to retask the strike platform from some other mission and the flight time required for the strike platform to arrive on station.

We assumed that the target is of high value and that the Air Force will in fact treat it as a time-sensitive target.[53] We also assumed that a strike aircraft is already on call and available to be retasked and that the commander at the combined air operations center has the authority to retask it without additional coordination. Even under these favorable conditions, however, it can take up to 5 min. to process the retasking request, up to 5 more min. to actually retask the aircraft; the aircraft still has to fly to arrive at its new station. Thus, it may take up to 10 min. to retask, plus flight time. The distance that the strike platform must fly is the governing factor in whether this CONOPS is possible, of course.

Because the times involved are comparable to those in the simulation, we cannot speak to this point directly. The reason is that we are looking at the long tail of the distribution of tracking

---

[53] Joint Publication 3-60, *Joint Targeting*, Washington, D.C.: Joint Chiefs of Staff, April 13, 2007, defines a *time-sensitive target* as a "joint force commander designated target requiring immediate response because it is a highly lucrative, fleeting target of opportunity or it poses (or will soon pose) a danger to friendly forces."

times: As noted earlier, when the RPA was able to establish a track for a few minutes, it rarely lost track afterward. This suggests that an RPA that has already tracked the target for 15 to 20 min. can likely continue to do so for quite some time—but how exactly long, we cannot say. In reality, Predators have been known to maintain track for much longer periods of time, such that even a retasking process requiring several hours still led to a successful kill. That such delays are outside the timeframe of the scenario we considered is a reminder that the hunter-killer scenario we examined is only one of many.

Although we did indeed model up to 45 min. of operations beyond the initial arrival of the target in the kill zone, we do not feel our FMV tracking model was sufficiently robust to explore that part of the scenario.[54] In our case, we imposed a strict, continuous identification requirement, meaning that the sensor operator effectively maintained eyes on target. Even so, however, the cumulative chance of an unlikely combination of events occurring that could break such a track, even when the vehicle is in view with high image quality, will grow over time—and we do not have a good model of such "clutter" for FMV. Furthermore, all our assumptions about image quality and enemy behaviors, which are already optimistic, become increasingly tenuous as the time frame lengthens. We can say, however, that 15 to 20 min. of tracking should allow, after the command and control times, at least 5 to 10 min. of flight time for the strike platform to arrive on station (assuming the call for fires is made promptly), which, as Figure 3.4 shows, still leaves considerable range of situations in which this CONOPS will succeed. More-favorable assumptions regarding command and control times could extend it further.

Measures of Effectiveness

We primarily examined two measures of effectiveness: the probability of identifying the target and the probability of successfully tracking it all the way to the designated kill zone. (A third measure, the average time required to identify the target, is discussed in the appendix. Given the short time constraints of the scenario, this measure ultimately did not prove to be of sufficient analytical value.)

Because we chose to calculate these two measures, the latter is contingent on the former. That is, in this scenario, a target would not be followed unless it could first be identified. This is a strong assumption that derives from the constraints of the scenario we modeled. Although it is perfectly reasonable to track an unidentified object—indeed, we implicitly assumed that the RPA sensor operator can "keep track of" the unidentified objects in his or her field of view by eye to zoom in on them one by one—in this scenario, there is a short time window in which the target is expected to be visible, and the FOV of the FMV sensor is small compared to the size of the cued

[54] The GMTI tracking model, while of course it could always stand improvement, is not relevant in Case 2 because the RPA concepts we looked at that were capable of carrying a GMTI sensor were also large enough to carry weapons.

Figure 3.4. Ranges from Flight Times for 547 kph True Airspeed (in minutes)

search area. As a result of these constraints, once the RPA ceases its raster search to follow a target, it is effectively committed. The odds of being able to recover from such a mistake in the time available are very small. Therefore, in our CONOPS, we assumed that the pilot would not divert to follow a target unless the sensor operator could confirm to a high degree of certainty (i.e., by identifying the target) that it was the right one. In a different hunter-killer scenario, such as one in which there is a better initial cue for the target or in which there is time to follow multiple targets, a looser CONOPS might well prove more effective.

Note, however, that all probabilities are reported in terms of the whole number of iterations, so if, in any particular instance, the probability of identification equals the probability of maintaining track, it is correct to infer that each target that was successfully identified was also successfully tracked.[55]

The probability of merely detecting the target (as opposed to identifying it) was not calculated separately and neither was the probability of classification. These were omitted because, under the assumption that positive identification of the target was the objective, we selected the flight profile and search pattern to provide sufficient image quality to make this possible.

[55] We did this to avoid reporting a probability of maintaining track that was higher than that of identification, which might leave the incorrect impression that some targets that were tracked were not identified. While it is certainly possible to track an unidentified target, especially with GMTI, success in the hunter-killer mission requires target identification.

4. Analysis and Results

Introduction

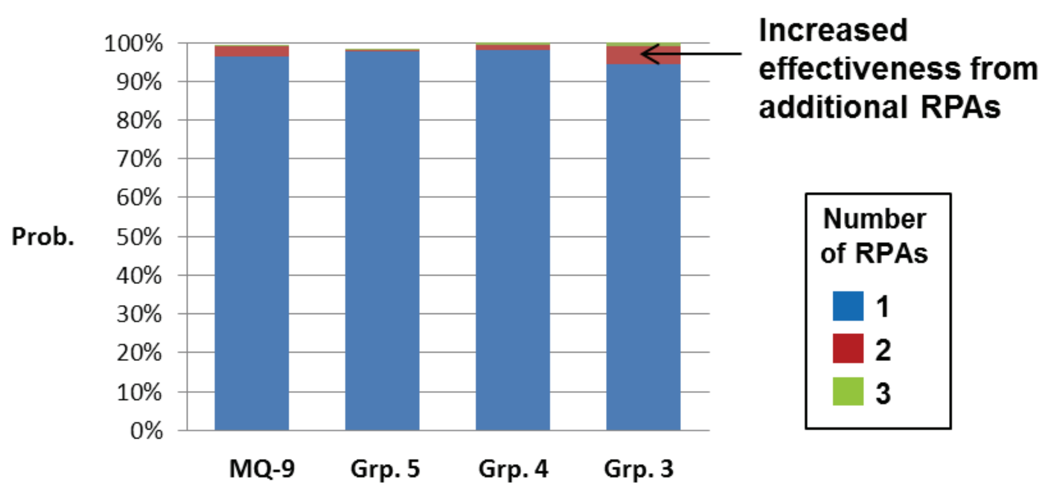
We assessed the operational effectiveness of the four different RPA concepts described in Chapter Two (MQ-9, Group 5, Group 4, and Group 3), employing a multiplicity of 1, 2, or 3 platforms at a time, under six different weather conditions, with two different NIIRS requirements, yielding a grand total of 144 variants. We typically ran 300 to 500 replications of each variant for the final production runs.[56] The full results are tabulated in the appendix. In this section, we summarize the results, pausing to discuss the more interesting outcomes.

Identifying and Tracking Probabilities

Clear Weather

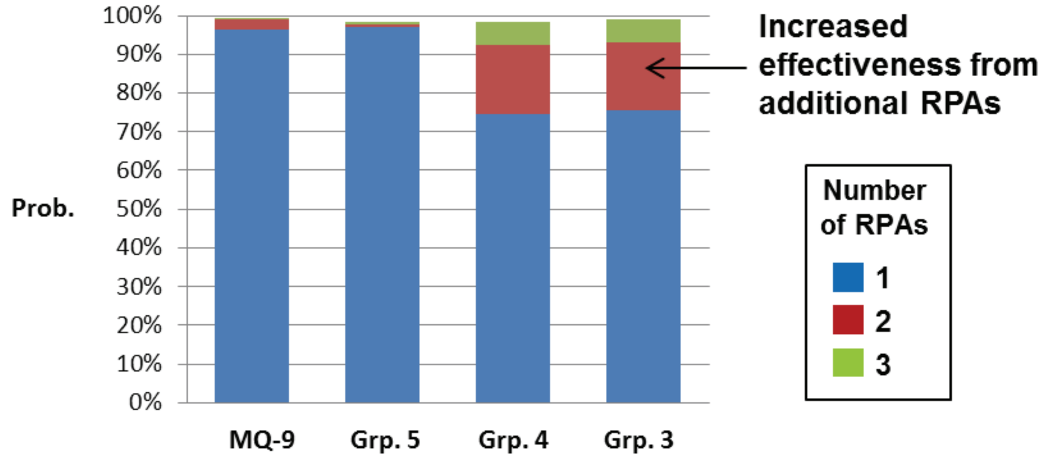
The most favorable conditions we considered were broad daylight, clear weather, and the lower NIIRS 7.0 requirement to identify the target. Under these conditions, as shown in Figures 4.1 and 4.2, all four RPA concepts performed very well in terms of both identifying and tracking the target. Groups 3 and 4 fared a bit worse than the others in terms of probability of tracking, but adding a second (or third) platform made up for this shortfall.

Figure 4.1. Probability of Identification in Broad Daylight, Clear Weather, with NIIRS 7.0 Identification Requirement



[56] Increasing to 1,000 replications refined the average results very little. Statistically, the "error" due to the smaller number of replications was less than 1 percent, but of course the uncertainty due to the many assumptions outlined in the previous two sections was more significant.

Figure 4.2. Probability of Maintaining Track in Broad Daylight, Clear Weather, with NIIRS 7.0 Identification Requirement



Under the same favorable environmental conditions, increasing the identification requirement to NIIRS 8.0 noticeably reduces the effectiveness of all single platforms, notably the smaller ones (Group 3 and Group 4), but having multiple platforms compensates for most or all of this drop in performance. The corresponding charts are shown in Figures 4.3 and 4.4.

Figure 4.3. Probability of Identification in Broad Daylight, Clear Weather, with NIIRS 8.0 Identification Requirement

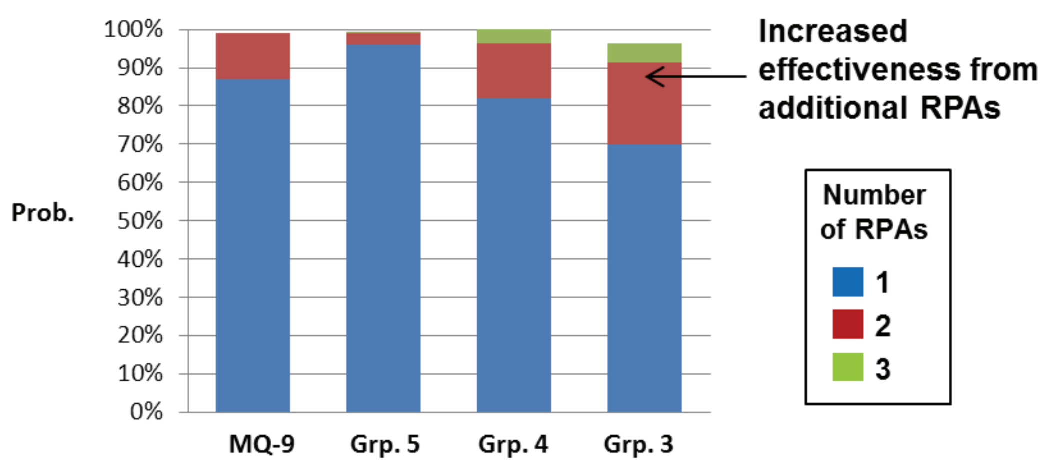
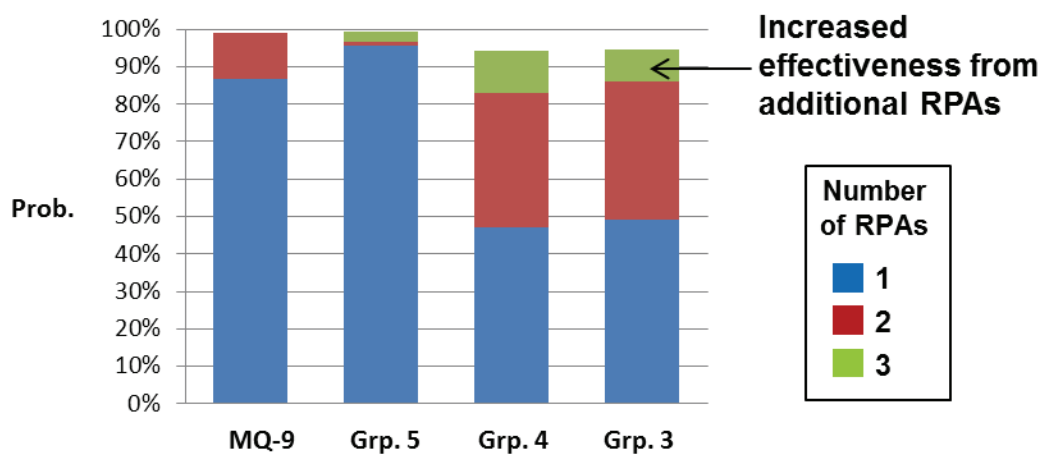


Figure 4.4. Probability of Maintaining Track in Broad Daylight, Clear Weather, with NIIRS 8.0 Identification Requirement



Most hunter-killer missions are currently conducted at night, however, due to the obvious desire to conceal the fact of surveillance from the target. So, we considered both day and night missions. Nighttime identifying and tracking performance for NIIRS 7.0 identification requirements are shown in Figures 4.5 and 4.6, respectively.

Figure 4.5. Probability of Identification at Night, for Clear Weather, with NIIRS 7.0 Identification Requirement

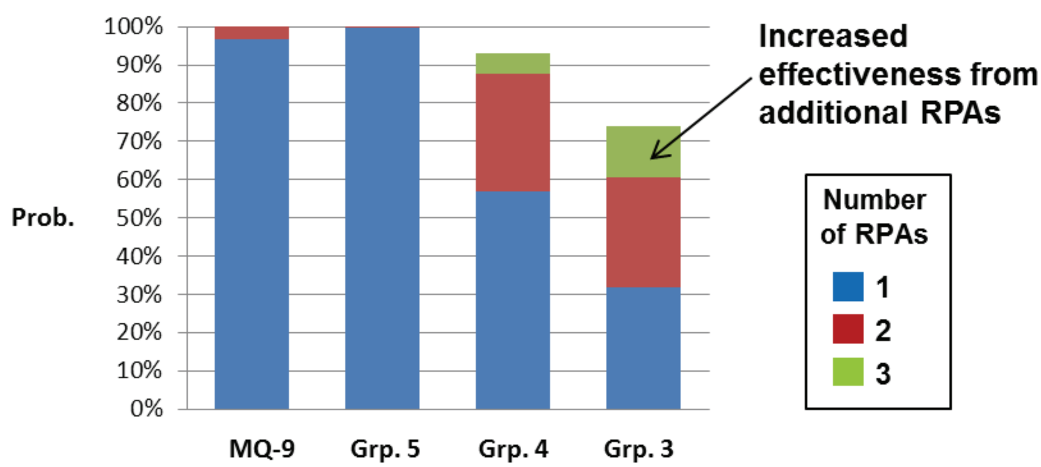
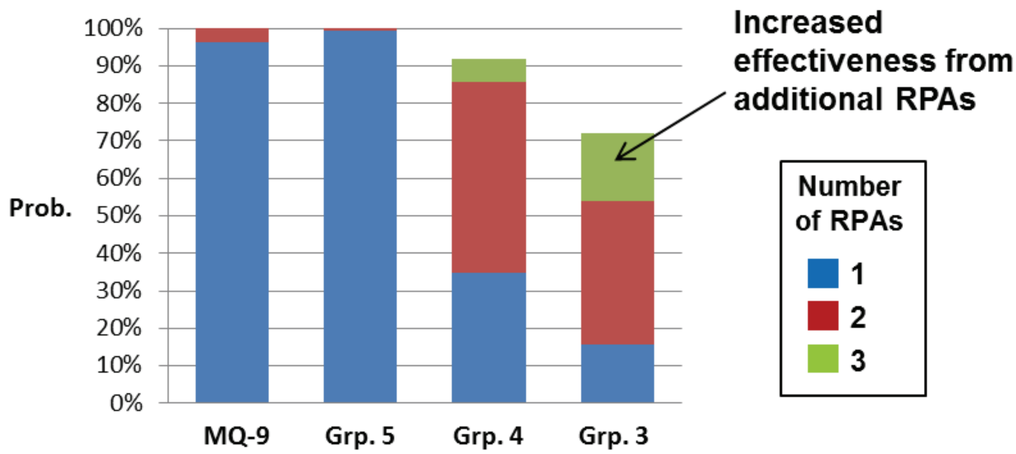


Figure 4.6. Probability of Maintaining Track at Night, for Clear Weather, with NIIRS 7.0 Identification Requirement



The MTS-B sensor package is unique among the sensors considered in that, in some of the medium-sized or wider viewing modes, the IR imaging quality is slightly superior to the EO imaging quality. The ability to find and identify any particular type of target, however, still depends on the target: As noted earlier, the NIIRS EO and IR scales are not quite identical in interpretation or requirements. In this particular case, however, a hot car engine at night is actually quite bright at IR wavelengths. The MQ-9 and the Group 5 concept therefore perform slightly better at night than they do during the day, under certain conditions.

Raven Eye I and Raven Eye II are general-purpose surveillance systems, however, and are not designed specifically for IR nighttime searching. Unlike the MTS-B, the IR image quality for these sensors is noticeably poorer than the corresponding EO image. The resulting flagging performance at night in the hunter-killer scenario we considered is evident. Even multiple Group 3 and Group 4 platforms cannot compensate for the loss of effectiveness because of the less capable IR sensors they are constrained to carry.

Moreover, the drop in performance for Groups 3 and 4 is due primarily to the need to fly at much lower altitudes to achieve the required image quality to identify the target. For this reason, it takes longer for them to search the area, so they have a greater likelihood of missing the target entirely. The tracking performance is affected similarly because, at lower altitudes, the field of view is smaller, and it is easier to lose the target when it makes an unexpected turn. Raising the altitude did not prove helpful because, in the event that the track *is* lost, the RPA must reacquire and reidentify.

The corresponding identification and tracking probabilities would be similarly pronounced for NIIRS 8.0 identification requirements (not shown).[57] As in the daylight case, much of the benefit of having additional platforms derives from the second platform; there is only marginal

[57] For this data, see the appendix.

improvement with the third. It is also worth noting that difficulties in tracking were almost always evident from the beginning of the replication, when the RPA attempted to follow the target out of the urban canyon in the early stages of the scenario. The upshot of this is that, if the RPA was in fact able to achieve a stable track on the target for the first few minutes, it was usually able to continue to do so throughout.

Fog

We considered a moderate fog with visibility that varied considerably with viewing angle and altitude. Depending on the circumstances, the transmittance ratio for visible wavelengths could vary from 0.0 (complete opacity) to about 0.5. The fog was more penetrable by IR wavelengths, which allowed approximately 0.9 transmittance for range of viewing angles (but still went to near-zero visibility for the most shallow viewing conditions).

The most significant effect of fog was on daytime EO sensors, with the more challenging NIIRS 8.0 requirement. The results for daytime identification and tracking probabilities are shown in Figures 4.7 and 4.8, respectively. The corresponding results for nighttime follow the same lines as those without fog, because IR sensors can penetrate fog more effectively than EO sensors can.

Figure 4.7. Probability of Identification for Daytime Fog, NIIRS 8.0 Requirement

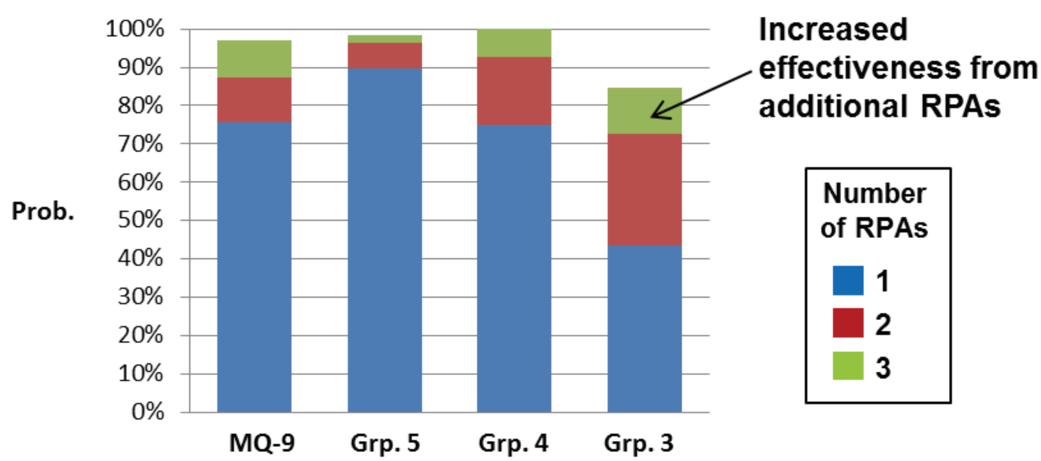
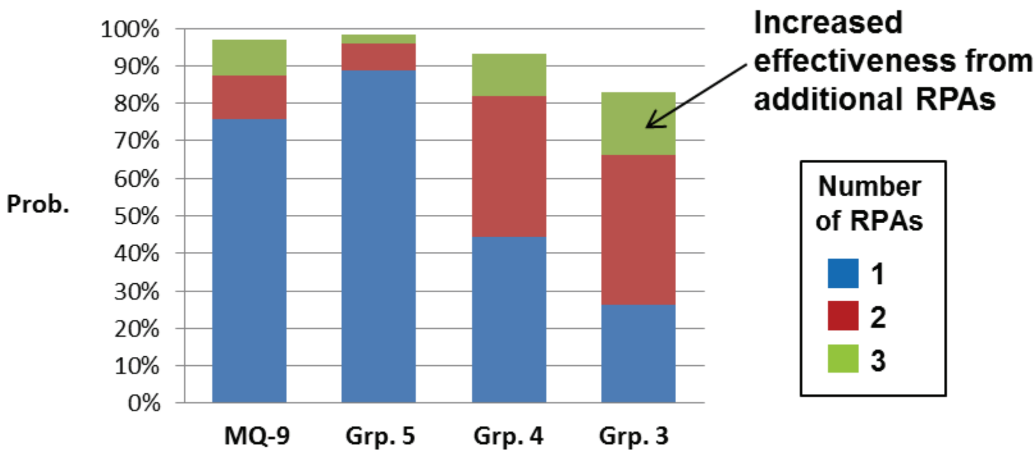


Figure 4.8. Probability of Maintaining Track for Daytime Fog, NIIRS 8.0 Requirement



Cloud Cover

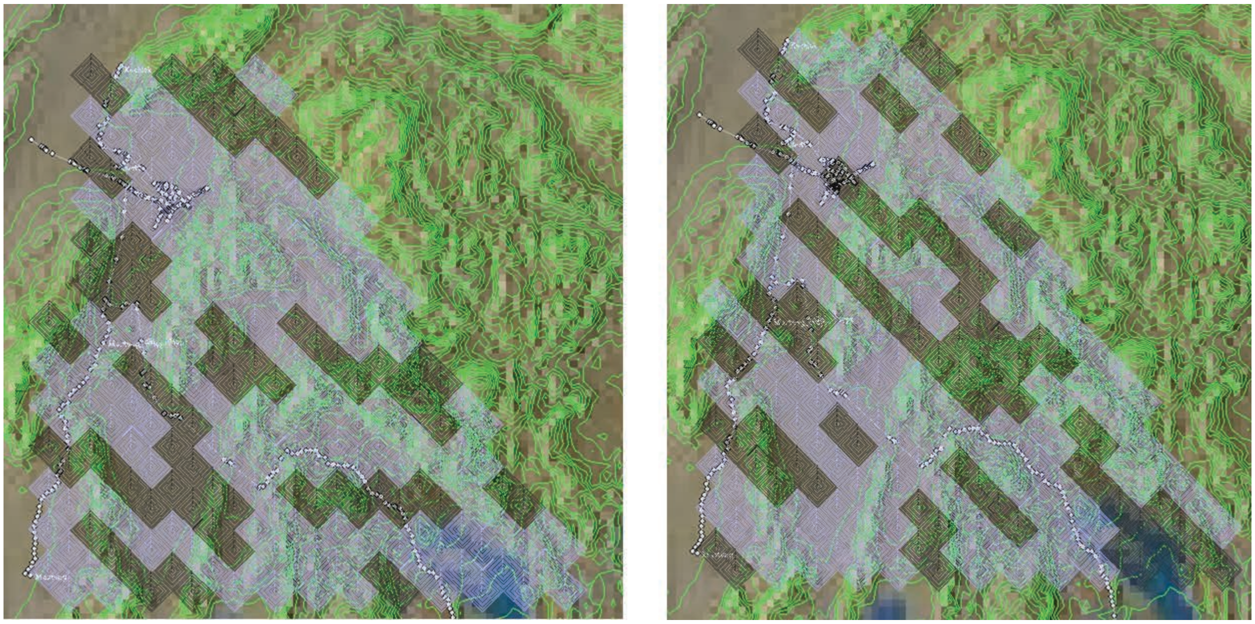
The performance of the RPAs under conditions of cloud cover is quite different from under conditions of fog. We took a partly cloudy sky of 40-percent average coverage, at a cloud ceiling of about 3,000 ft. above the terrain.[58] Two examples of the terrain with cloud coverage, at different times, are shown in Figure 4.9. The cloud cover pattern changed slowly throughout the simulation.

The probabilities of finding and identifying the target and of maintaining track through the urban canyon to the target's destination are shown in Figures 4.10 and 4.11. Because the MQ-9 and Group 5 concepts were equipped with the Lynx GMTI/SAR radar system (in addition to the FMV modality), they were able to penetrate the cloud cover to maintain track (although not for identification because that still required a solid image in EO or IR). Given that the conditions were not fully cloudy, it was advantageous for these two larger RPAs to continue to fly above the clouds, as though the clouds were absent. However, the Group 3 and Group 4 concepts, which did not have radar capabilities, needed to fly below the clouds, otherwise they would be completely ineffective. These choices had a significant effect on the results. In the cases shown here, the Group 3 concepts outperform Group 4 somewhat because of improved maneuverability at slower speeds; however, at night (see the appendix), this relative performance is reversed because the improved IR capabilities of the heavier sensor package on the Group 4 aircraft become the controlling factor.

---

[58] We used the center of the urban area as the reference point. As the target headed toward more-mountainous rural areas, the effective height of the cloud ceiling changed as the road rose. Generally speaking, the effective height of the cloud ceiling was lower in rural areas.

Figure 4.9. Cloud Cover over the Region of Interest at Different Times



NOTE: Black is obscure; pale blue is clear sky. Terrain is also shown.

Figure 4.10. Probability of Identification in Daytime, with Clouds, NIIRS 7.0 Identification Requirement

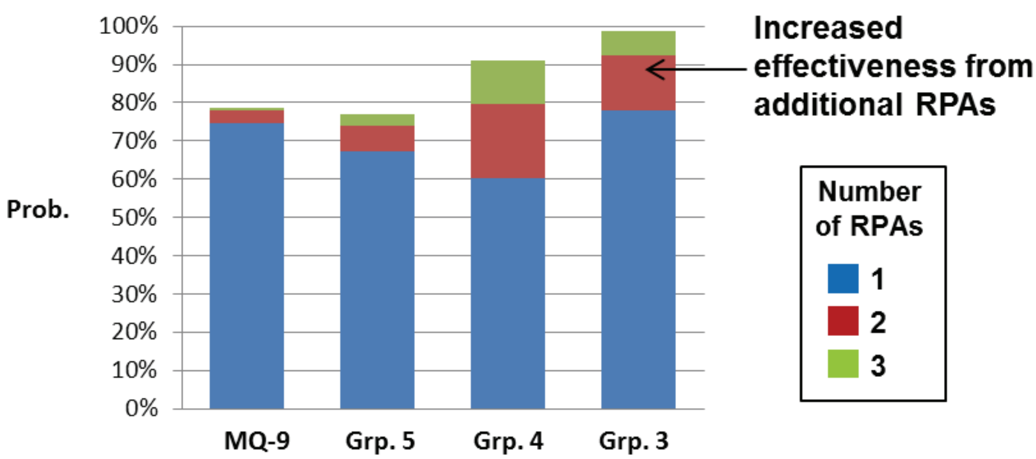
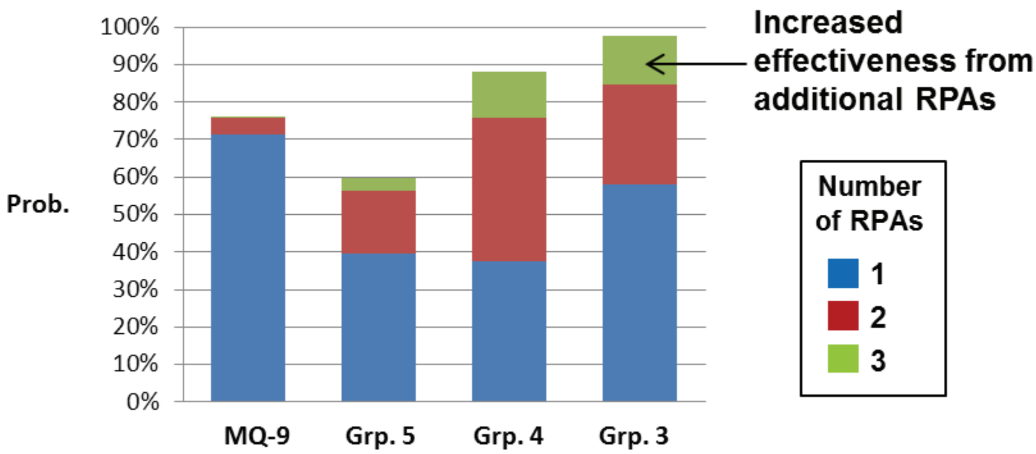


Figure 4.11. Probability of Maintaining Track on Target in Daytime, with Clouds, NIIRS 7.0 Identification Requirement



One unexpected result is that the MQ-9 was the best *single* platform in terms of maintaining track and was nearly tied for best as a single platform in terms of identifying the target. One interpretation of these results, which we discuss further in Chapter Four, is that the MQ-9 was developed for this particular kind of mission in Iraq and Afghanistan. However, adding additional Group 3 and Group 4 platforms significantly increased effectiveness, while adding additional MQ-9 platforms gained little. This is because these two smaller groups fly below the clouds, and therefore it is the altitude that restricts them, rather than the blockage of LOS.

The situation becomes clearer if we look at the nighttime figures. As noted earlier, many missions in Iraq and Afghanistan were night missions, and the MTS-B sensor has unusually powerful IR capabilities. Figures 4.12 and 4.13 show the probabilities of identifying and maintaining track, respectively. For a *single* platform, the MQ-9 is best in both measures but ends up in the middle of the pack with others when multiple platforms are considered.

One feature of interest is that the Group 5 platform does poorest in tracking in daytime and nighttime cases. This is because the Group 5 platform we modeled, a jet, has a minimum speed that is much faster than that of the vehicle it is attempting to track (see Table 1.1). This mismatch in velocities makes tracking difficult. As a result, the Group 5 platform loses the target more frequently behind clouds and is forced into unfavorable geometries more often as it tries to keep the target in view. It is also not clear that it can react to changes in target movement as effectively.

Figure 4.12. Probability of Identification at Night, with Clouds, NIIRS 7.0 Identification Requirement

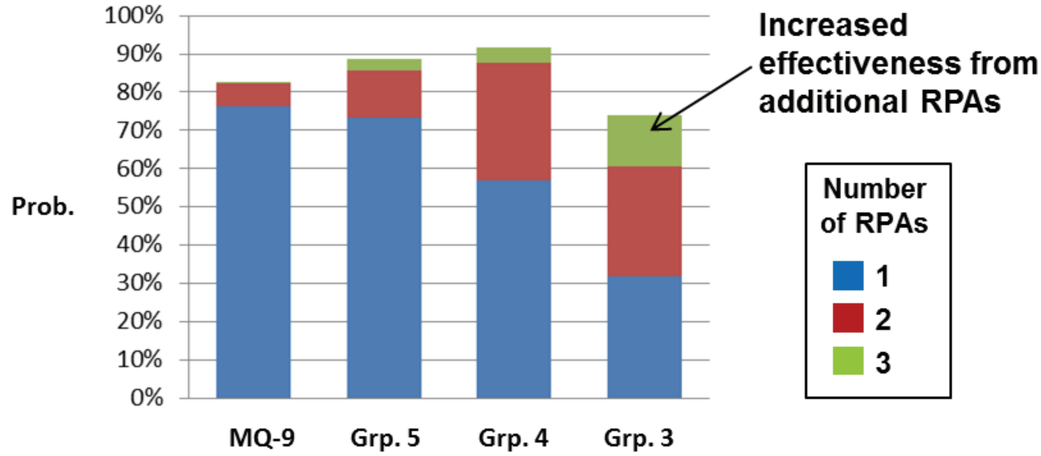
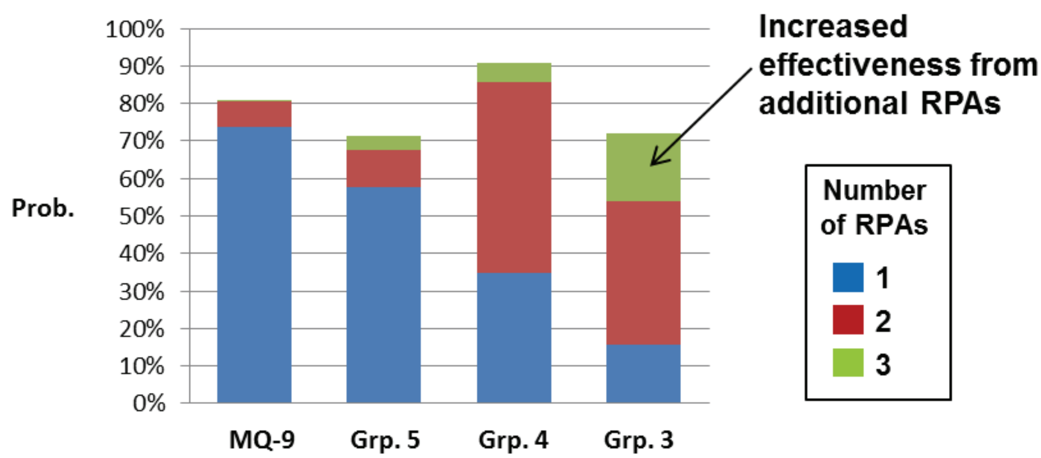


Figure 4.13. Probability of Maintaining Track on Target at Night, with Clouds, NIIRS 7.0 Identification Requirement



Summary Figures

The following stoplight charts summarize the operational effectiveness of all cases considered in this analysis. We show here the results for one platform and for three platforms. (The appendix offers the intermediate results for two platforms.) Results for the probability of identification are shown in Figure 4.14.

A similar chart for maintaining track is shown in Figure 4.15. In both charts, the inability of a *single* Group 3 or Group 4 RPA concept to fulfill mission requirements is evident, but the remarkable improvement due to employing multiple platforms in a cooperative fashion is evident as well.

Figure 4.14. Summary of Probability of Identification, All Cases, for One or Three RPAs

	Weather	NIIRS ID Req.	1 RPA Base	1 RPA Gr-5	1 RPA Gr-4	1 RPA Gr-3	3 RPAs Base	3 RPAs Gr-5	3 RPAs Gr-4	3 RPAs Gr-3
Day	Clear	7.0	G	G	G	G	G	G	G	G
		8.0	Y	G	Y	O	G	G	G	G
	Fog	7.0	G	G	G	Y	G	G	G	G
		8.0	O	Y	O	B	G	G	G	Y
	Cloud	7.0	O	O	R	O	O	O	G	G
		8.0	R	O	R	O	O	O	G	G
Night	Clear	7.0	G	G	R	R	G	G	G	G
		8.0	G	G	B	B	G	G	Y	O
	Fog	7.0	G	G	R	B	G	G	G	O
		8.0	G	G	R	B	G	G	G	O
	Cloud	7.0	O	O	R	B	Y	Y	G	O
		8.0	R	O	R	B	O	Y	G	O

Scale (%)	
G	90 – 100
Y	80 – 90
O	70 – 80
R	50 – 70
B	0 – 50

Figure 4.15. Summary of Probability of Maintaining Track, All Cases, for One or Three RPAs

	Weather	NIIRS ID Req.	1 RPA Base	1 RPA Gr-5	1 RPA Gr-4	1 RPA Gr-3	3 RPAs Base	3 RPAs Gr-5	3 RPAs Gr-4	3 RPAs Gr-3
Day	Clear	7.0	G	G	O	O	G	G	G	G
		8.0	Y	G	B	B	G	G	G	G
	Fog	7.0	G	G	R	B	G	G	G	G
		8.0	O	Y	B	B	G	G	G	Y
	Cloud	7.0	O	B	B	R	O	R	Y	G
		8.0	R	B	B	B	O	R	Y	G
Night	Clear	7.0	G	G	R	B	G	G	G	O
		8.0	G	G	B	B	G	G	G	O
	Fog	7.0	G	G	B	B	G	G	Y	R
		8.0	G	G	B	B	G	G	Y	R
	Cloud	7.0	O	R	B	B	O	O	G	Y
		8.0	R	R	B	B	O	R	G	Y

Scale (%)	
G	90 – 100
Y	80 – 90
O	70 – 80
R	50 – 70
B	0 – 50

5. Conclusion

Findings

Analysis of the modeling results leads us to four broad findings.

First, *there is no silver bullet*. Even in this one particular type of one particular hunter-killer mission, no single RPA concept performed well on all measures under all environmental conditions. In fact, there is at least one case in which each of the four RPA concepts performed better than the others. For example, with multiple aircraft, the low-flying Group 3 performed better at tracking and identification under cloud cover during the day, but Group 4 was somewhat better with cloud cover at night. Meanwhile, Group 5 generally performed best in terms of probability of identification, but the MQ-9 edged it out in some situations when it comes to probability of maintaining track. Note, however, that platforms with inferior sensors must fly at lower altitudes to achieve the required resolution, which clearly would entail greater survivability concerns in any threat environment other than the permissive environment we considered.

Second, *numbers can compensate for capability*. Despite their inferior-resolution sensor suites, multiple smaller RPAs (Groups 3 and 4) equaled or exceeded the performance of single larger RPAs in many environmental conditions (MQ-9 and Group 5), especially in the case of cloud cover.[59] The only clear exception, however, is at night, when the superior MTS-B IR sensor demonstrated a clear advantage. With sufficient numbers, all platforms are able to detect, identify, and track the target for at least 15 min.—long enough for to achieve a kill by another fighter within 50 nmi, including the time required to complete all command and control processes (on average). Multiple platforms are also less likely to lose targets in the urban canyon, thanks to multiple viewpoints. Smaller RPAs may also be able to augment capabilities against smart, sophisticated adversaries.

Third, *the MQ-9 Reaper holds up well against the other RPA design concepts we modeled in this scenario*. The MQ-9 scored comparably to other options under most environmental conditions. It rarely outperformed all other platforms but betrayed no Achilles' heel: The MQ-9 was never dramatically outperformed and never fared worst on any measure. It was the only one of the four RPA concepts considered that never demonstrated a probability of identification or probability of maintaining track of less than 50 percent as a single platform. (Multiple platforms increase the scores.) The ability to fly significantly slower, along with a tighter turn radius,

[59] We used an obscuration of 40 percent. Although we did not simulate more opaque cloud cover conditions, we believe it likely that the Group 3 and Group 4 platforms would also perform well in those cases.

allows MQ-9 to track ground vehicles well; the MTS-B and Lynx combination provides night-time, fog, and partial cloud-cover capabilities.[60]

Finally, *improving MQ-9 sensor capabilities may be a cost-effective option*. Although we did not perform a cost-effectiveness analysis, it appears that upgrading the existing MQ-9 platform in this way may be a preferred way, given budget constraints, to achieve moderately enhanced operational effectiveness in similar scenarios.

One modest enhancement would be to make the MTS-B sensor package more flexible by adding variable (as opposed to fixed) levels of magnification. Neither the EO nor IR video cameras on the MTS-B are capable of continuous zoom—the MTS-B allows only fixed levels of magnification—and the platform was thus often unable to take advantage of a "sweet spot" for this mission in terms of altitude and flight pattern. This would have improved the CONOPS and altered the flight profiles.

A more-significant enhancement would be to improve the effective image quality of MTS-B video by +1.0 NIIRS.[61] This would not merely improve the picture on the screen but, more important, would permit greater operational flexibility. An improvement of +1.0 NIIRS would allow the Reaper to identify the target at nearly twice the altitude under many conditions. This would allow the platform not only to search more effectively but to track more effectively because it would not be as vulnerable to losing a target that changed its route unexpectedly, and the higher vantage point would afford greater visibility into the urban canyon. It would also improve survivability. Along the same lines, an improved WAMI sensor, with enhanced NIIRS image quality, could prove very useful as well, provided that PED resources were also available to handle the higher data rate.

Areas for Further Analysis

One excursion we did not consider was pairing different RPA classes together. In particular, we did not consider the advantages of having one smaller RPA fly below the clouds while a larger one flew above. Once the CONOPS for such a mission are understood, this would be an important case, looking to see if synergies between the two different classes can be demonstrated, at least in this relatively simple scenario.

We also looked at only one particular version of cloud cover, yet the ceiling and opacity can vary considerably, and we also looked only at one instance of fog. While the results suggest that increasing the intensity of fog would produce fairly straightforward extrapolation, it is not clear how the balance between flying above and below the clouds would work for more-challenging cloud cover situations. In very opaque cases with higher cloud cover, it may be sensible for the

[60] It does not provide all-weather capabilities. As was pointed out to us by more than one Air Force officer, there is always a reasonable combination of weather that can thwart airborne ISR operations.

[61] Greater improvements in NIIRS are of course more desirable, but even a single level of improvement would make a big difference.

MQ-9 and even Group 5 to fly below the cloud ceiling, but we did not demonstrate that in this report.

More important, we employed a simple CONOPS for the enemy that was neither adaptive nor reactive. Other than occasionally stopping to attempt to elude pursuit, the target in this scenario did not use camouflage or concealment. We also did not consider the possibility that the targeted individual could hear or see the RPA tracking him or her and respond by hiding or changing vehicles.[62] Modeling a more-intelligent or more-cautious enemy would be a valuable addition. A more-robust tracking model would also be necessary in that case.

We also did not model the Gorgon Stare or future WAMI sensors, largely because of a lack of a satisfactory model for the PED resources required. To make a fair comparison between WAMI sensors and the others we considered would have required addressing these PED issues, and we chose not to focus on that area. As WAMI sensors are now on the battlefield, this is an important area for future research.

We also did not consider upgraded versions of the sensors we did model. To the extent that such upgrades would merely increase the image quality at a given altitude, the performance can be extrapolated easily. However, in some cases, dramatically improved sensor performance might permit the RPA to take advantage of different CONOPS to achieve even greater operational effectiveness. Enhancing the modeling effort to account for more-capable enemies, and more-capable assets, would be another important future contribution to the analysis of hunter-killer and similar missions.

[62] The success of counterterrorism operations with the MQ-1 and MQ-9 in Iraq and Afghanistan demonstrates that they are generally able to fly such that they are difficult to see or hear, especially in an urban environment—and previous methodology work on aural detection is not inconsistent with this—but we have no such evidence for either the much-lower-flying Group 3 and Group 4 in this type of mission.

Appendix. Full Results

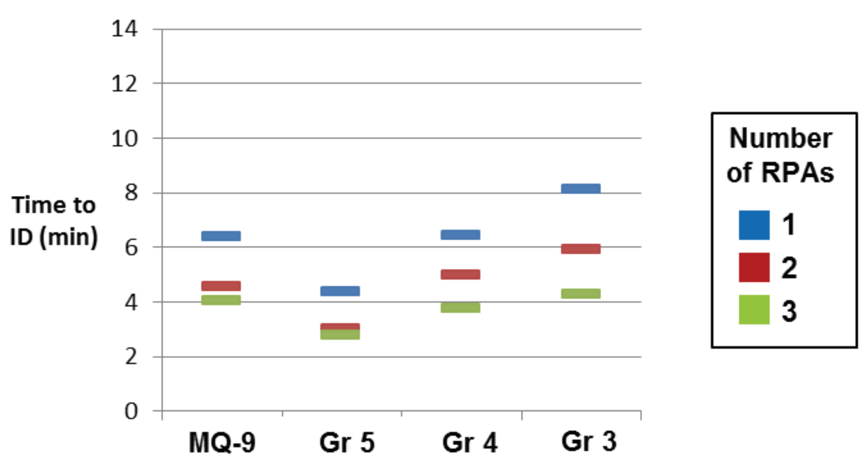
Before presenting the complete numerical modeling results, we will introduce and describe a third measure of effectiveness—the time to identification—which is included here alongside the two measures reported in the body of the report. Although this measure was excluded from the write-up because it ultimately lacked sufficient analytical value, we include it here in the interests of completeness and because it may offer insights into the modeling approach.

Time to identification is defined as the total elapsed time between the emergence of the target from its (random) hiding place and its initial identification by the RPA sensor operator. Note that only the first successful identification is included. If the target is lost and must be reacquired, the measure is not reset.

Because this metric is contingent on the probability of identification, this creates some unwelcome artifacts. In particular, the average time to identification occasionally appears to be slightly *worse* (higher) when additional platforms are added. This is because they are able to locate the target vehicle under more challenging conditions—and when these harder-won successes are added to the sample, it can skew the average time to identification upward.

The results for the best viewing conditions (daytime and clear weather) and least stringent identification requirements (NIIRS 7.0) are shown in Figure A.1. In this situation, nearly all platforms saw all targets, so the results are straightforward: The platforms that moved the fastest (Group 5) were the first to identify, and adding extra platforms reduced the time to identification similarly.

Figure A.1. Average Time to Identification in Broad Daylight, Clear Weather, with NIIRS 7.0 Identification Requirement



Adding fog, changing to nighttime operations, or raising the NIIRS identification threshold to 8.0 does not alter this underlying pattern. In most cases, the pattern is instead exaggerated. As an illustration, Figure A.2 shows the results of including all three changes at once.

The results for the Group 3 aircraft illustrate the artifact mentioned previously. The performance of a single Group 3 aircraft was so poor (29 percent) that the only targets it could identify were those that were easiest to find. Adding a second or third RPA immediately bumped the identification rate over 70 percent, and the sample then included more of the targets that innately took longer to identify.

Cloud cover noticeably shifts the overall pattern, however. The results for cloud cover, daylight, and NIIRS 8.0 identification threshold are shown in Figure A.3. In this variant, Groups 3 and 4 can achieve faster identification times because they fly beneath the clouds; in contrast, the MQ-9 and Group 5 platform must wait for the target to pass through a break in the clouds to positively identify it with FMV. Although, in principle, the MQ-9 and Group 5 can fly beneath the clouds, the cloud ceiling we modeled was very low (3,000 ft.), and this is generally considered impractical. Operating one of these large RPAs so close to the ground also would have violated our assumption that the enemy could not see or hear it.

Figure A.2. Average Time to Identification at Night, with Fog, with NIIRS 8.0 Identification Requirement

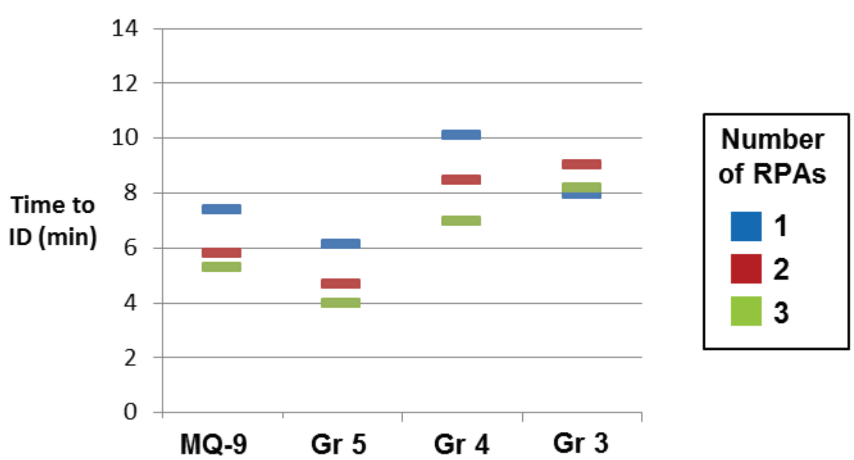
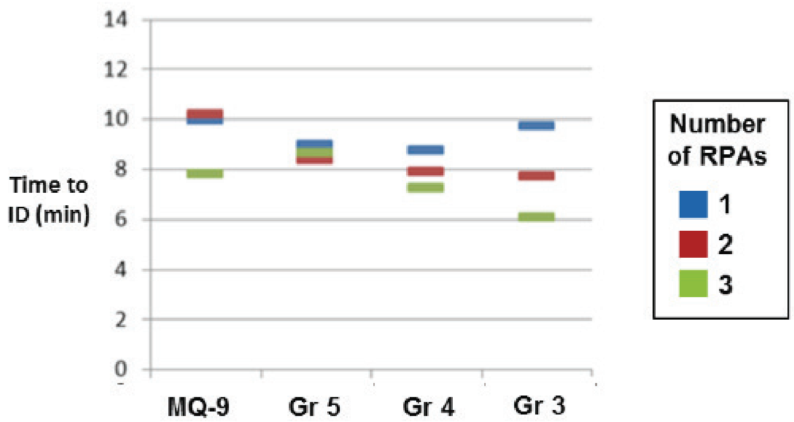


Figure A.3. Average Time to Identification in Broad Daylight, with Clouds, with NIIRS 8.0 Identification Requirement



Further results for this metric may be found in Table A.1, which summarizes the outcomes of all three measures of effectiveness for all cases. In this table, "Found" and "Tracked" refer to the probability of identification and the probability of following the target vehicle all the way to the kill zone, respectively. "Avg. Time to ID" refers to the third metric discussed above. A fourth statistic, "Avg. Track Duration," refers only to the lengths of tracks that were not ultimately successful. In some cases, no figure is provided, because every identified target was also successfully tracked all the way to the kill zone. Because this statistic depends so strongly on the arbitrary starting and ending points for the particular replications, it has very limited analytic value and is essentially useful only for diagnostic purposes. We included it here for reference only.

Table A.1. Numerical Modeling Results

Time	Weather	ID Req.	Platform	Multiplicity	Found (percent)	Tracked (percent)	Avg. Track Duration (min.)	Avg. Time to ID (min.)
Day	Clear	NIIRS 7.0	MQ-9	1	96	96	24.71	6.39
Day	Clear	NIIRS 7.0	MQ-9	2	99	99	20.46	4.58
Day	Clear	NIIRS 7.0	MQ-9	3	99	99	27.85	4.05
Day	Clear	NIIRS 7.0	Group 5	1	98	97	25.70	4.35
Day	Clear	NIIRS 7.0	Group 5	2	98	98	23.56	2.99
Day	Clear	NIIRS 7.0	Group 5	3	98	98	34.45	2.79
Day	Clear	NIIRS 7.0	Group 4	1	98	75	18.94	6.44
Day	Clear	NIIRS 7.0	Group 4	2	99	92	18.55	4.98
Day	Clear	NIIRS 7.0	Group 4	3	100	98	23.03	3.76
Day	Clear	NIIRS 7.0	Group 3	1	94	76	21.50	8.12
Day	Clear	NIIRS 7.0	Group 3	2	99	93	16.52	5.92
Day	Clear	NIIRS 7.0	Group 3	3	100	99	13.15	4.27
Day	Clear	NIIRS 8.0	MQ-9	1	87	87	37.15	8.78
Day	Clear	NIIRS 8.0	MQ-9	2	99	99	—	6.43
Day	Clear	NIIRS 8.0	MQ-9	3	99	99	21.13	4.68
Day	Clear	NIIRS 8.0	Group 5	1	96	96	22.98	6.67
Day	Clear	NIIRS 8.0	Group 5	2	99	97	31.47	4.23
Day	Clear	NIIRS 8.0	Group 5	3	99	99	—	4.65
Day	Clear	NIIRS 8.0	Group 4	1	82	47	22.91	8.99
Day	Clear	NIIRS 8.0	Group 4	2	96	83	20.91	6.88
Day	Clear	NIIRS 8.0	Group 4	3	100	94	21.57	5.20
Day	Clear	NIIRS 8.0	Group 3	1	70	49	25.94	9.57
Day	Clear	NIIRS 8.0	Group 3	2	91	86	24.69	8.08
Day	Clear	NIIRS 8.0	Group 3	3	96	95	28.11	7.09
Day	Clouds	NIIRS 7.0	MQ-9	1	75	71	24.50	8.54
Day	Clouds	NIIRS 7.0	MQ-9	2	78	76	32.63	10.02
Day	Clouds	NIIRS 7.0	MQ-9	3	79	76	36.83	10.25
Day	Clouds	NIIRS 7.0	Group 5	1	67	40	20.30	5.35
Day	Clouds	NIIRS 7.0	Group 5	2	74	56	21.91	6.02
Day	Clouds	NIIRS 7.0	Group 5	3	77	60	24.53	4.71
Day	Clouds	NIIRS 7.0	Group 4	1	60	38	23.66	9.03
Day	Clouds	NIIRS 7.0	Group 4	2	80	76	32.04	7.57
Day	Clouds	NIIRS 7.0	Group 4	3	91	88	29.18	6.81
Day	Clouds	NIIRS 7.0	Group 3	1	78	58	26.20	9.40
Day	Clouds	NIIRS 7.0	Group 3	2	92	85	27.33	6.95
Day	Clouds	NIIRS 7.0	Group 3	3	99	98	31.48	5.50

Table A.1—Continued

Time	Weather	ID Req.	Platform	Multiplicity	Found (percent)	Tracked (percent)	Avg. Track Duration (min.)	Avg. Time to ID (min.)
Day	Clear	NIIRS 8.0	MQ-9	1	62	59	28.87	9.97
Day	Clear	NIIRS 8.0	MQ-9	2	76	75	30.76	10.20
Day	Clear	NIIRS 8.0	MQ-9	3	79	77	35.39	7.82
Day	Clouds	NIIRS 8.0	Group 5	1	72	50	18.35	8.96
Day	Clouds	NIIRS 8.0	Group 5	2	77	60	22.04	8.37
Day	Clouds	NIIRS 8.0	Group 5	3	77	61	25.03	8.64
Day	Clouds	NIIRS 8.0	Group 4	1	57	36	22.28	8.74
Day	Clouds	NIIRS 8.0	Group 4	2	81	74	31.41	7.90
Day	Clouds	NIIRS 8.0	Group 4	3	94	92	27.86	7.26
Day	Clouds	NIIRS 8.0	Group 3	1	70	47	22.57	9.75
Day	Clouds	NIIRS 8.0	Group 3	2	91	82	14.78	7.70
Day	Clouds	NIIRS 8.0	Group 3	3	95	95	60.33	6.06
Day	Fog	NIIRS 7.0	MQ-9	1	94	94	29.46	8.20
Day	Fog	NIIRS 7.0	MQ-9	2	100	100	—	5.34
Day	Fog	NIIRS 7.0	MQ-9	3	100	99	33.00	3.99
Day	Fog	NIIRS 7.0	Group 5	1	99	99	22.57	4.75
Day	Fog	NIIRS 7.0	Group 5	2	100	100	22.66	4.59
Day	Fog	NIIRS 7.0	Group 5	3	100	99	21.07	3.27
Day	Fog	NIIRS 7.0	Group 4	1	96	57	22.97	7.39
Day	Fog	NIIRS 7.0	Group 4	2	97	85	15.52	7.60
Day	Fog	NIIRS 7.0	Group 4	3	100	99	18.03	4.16
Day	Fog	NIIRS 7.0	Group 3	1	80	49	20.55	9.52
Day	Fog	NIIRS 7.0	Group 3	2	98	84	19.71	6.49
Day	Fog	NIIRS 7.0	Group 3	3	100	98	17.34	5.28
Day	Fog	NIIRS 8.0	MQ-9	1	76	76	29.57	7.65
Day	Fog	NIIRS 8.0	MQ-9	2	87	87	67.37	7.12
Day	Fog	NIIRS 8.0	MQ-9	3	97	97	38.86	5.82
Day	Fog	NIIRS 8.0	Group 5	1	90	89	36.73	6.32
Day	Fog	NIIRS 8.0	Group 5	2	96	96	73.96	4.90
Day	Fog	NIIRS 8.0	Group 5	3	98	98	—	4.16
Day	Fog	NIIRS 8.0	Group 4	1	75	44	20.86	9.92
Day	Fog	NIIRS 8.0	Group 4	2	93	82	28.81	7.28
Day	Fog	NIIRS 8.0	Group 4	3	100	93	11.27	6.43
Day	Fog	NIIRS 8.0	Group 3	1	44	26	26.15	10.44
Day	Fog	NIIRS 8.0	Group 3	2	73	66	24.51	7.72
Day	Fog	NIIRS 8.0	Group 3	3	84	83	27.43	6.90

Table A.1—Continued

Time	Weather	ID Req.	Platform	Multiplicity	Found (percent)	Tracked (percent)	Avg. Track Duration (min.)	Avg. Time to ID (min.)
Night	Clear	NIIRS 7.0	MQ-9	1	97	96	34.18	7.83
Night	Clear	NIIRS 7.0	MQ-9	2	100	100	26.64	5.59
Night	Clear	NIIRS 7.0	MQ-9	3	100	100	26.74	4.09
Night	Clear	NIIRS 7.0	Group 5	1	100	99	25.44	4.97
Night	Clear	NIIRS 7.0	Group 5	2	100	100	19.77	4.44
Night	Clear	NIIRS 7.0	Group 5	3	100	100	29.18	3.11
Night	Clear	NIIRS 7.0	Group 4	1	57	35	27.94	9.65
Night	Clear	NIIRS 7.0	Group 4	2	88	86	28.47	8.17
Night	Clear	NIIRS 7.0	Group 4	3	93	92	30.90	6.30
Night	Clear	NIIRS 7.0	Group 3	1	32	16	26.45	5.96
Night	Clear	NIIRS 7.0	Group 3	2	61	54	35.71	7.83
Night	Clear	NIIRS 7.0	Group 3	3	74	72	26.10	6.99
Night	Clear	NIIRS 8.0	MQ-9	1	92	91	42.22	7.29
Night	Clear	NIIRS 8.0	MQ-9	2	98	98	36.47	5.84
Night	Clear	NIIRS 8.0	MQ-9	3	99	99	34.88	5.27
Night	Clear	NIIRS 8.0	Group 5	1	97	97	22.63	6.11
Night	Clear	NIIRS 8.0	Group 5	2	100	98	21.86	4.73
Night	Clear	NIIRS 8.0	Group 5	3	99	99	—	5.43
Night	Clear	NIIRS 8.0	Group 4	1	60	40	26.50	10.25
Night	Clear	NIIRS 8.0	Group 4	2	86	81	26.79	8.38
Night	Clear	NIIRS 8.0	Group 4	3	97	96	25.92	6.69
Night	Clear	NIIRS 8.0	Group 3	1	36	18	28.18	8.27
Night	Clear	NIIRS 8.0	Group 3	2	69	64	38.96	9.10
Night	Clear	NIIRS 8.0	Group 3	3	82	81	31.79	7.96
Night	Clouds	NIIRS 7.0	MQ-9	1	76	74	26.18	11.63
Night	Clouds	NIIRS 7.0	MQ-9	2	82	81	32.30	10.18
Night	Clouds	NIIRS 7.0	MQ-9	3	81	80	35.40	9.31
Night	Clouds	NIIRS 7.0	Group 5	1	73	58	21.21	8.60
Night	Clouds	NIIRS 7.0	Group 5	2	86	68	23.04	8.43
Night	Clouds	NIIRS 7.0	Group 5	3	89	71	24.36	9.11
Night	Clouds	NIIRS 7.0	Group 4	1	57	35	27.94	9.65
Night	Clouds	NIIRS 7.0	Group 4	2	88	86	28.47	8.17
Night	Clouds	NIIRS 7.0	Group 4	3	92	91	35.93	6.27
Night	Clouds	NIIRS 7.0	Group 3	1	32	16	26.45	5.96
Night	Clouds	NIIRS 7.0	Group 3	2	61	54	35.71	7.83
Night	Clouds	NIIRS 7.0	Group 3	3	74	72	26.10	6.99

Table A.1—Continued

Time	Weather	ID Req.	Platform	Multiplicity	Found (percent)	Tracked (percent)	Avg. Track Duration (min.)	Avg. Time to ID (min.)
Night	Clouds	NIIRS 8.0	MQ-9	1	60	58	31.23	9.35
Night	Clouds	NIIRS 8.0	MQ-9	2	73	71	33.62	9.46
Night	Clouds	NIIRS 8.0	MQ-9	3	81	79	34.32	8.01
Night	Clouds	NIIRS 8.0	Group 5	1	73	54	18.42	8.87
Night	Clouds	NIIRS 8.0	Group 5	2	84	68	24.32	8.62
Night	Clouds	NIIRS 8.0	Group 5	3	88	75	23.88	8.06
Night	Clouds	NIIRS 8.0	Group 4	1	59	32	27.84	10.21
Night	Clouds	NIIRS 8.0	Group 4	2	86	81	26.79	8.38
Night	Clouds	NIIRS 8.0	Group 4	3	93	92	20.37	6.39
Night	Clouds	NIIRS 8.0	Group 3	1	26	13	20.85	6.92
Night	Clouds	NIIRS 8.0	Group 3	2	67	60	37.57	9.91
Night	Clouds	NIIRS 8.0	Group 3	3	79	78	43.72	7.86
Night	Fog	NIIRS 7.0	MQ-9	1	94	93	31.19	7.95
Night	Fog	NIIRS 7.0	MQ-9	2	99	99	22.00	5.75
Night	Fog	NIIRS 7.0	MQ-9	3	100	99	29.45	4.17
Night	Fog	NIIRS 7.0	Group 5	1	99	99	29.64	5.04
Night	Fog	NIIRS 7.0	Group 5	2	100	100	31.43	4.53
Night	Fog	NIIRS 7.0	Group 5	3	100	100	29.99	3.29
Night	Fog	NIIRS 7.0	Group 4	1	55	35	30.89	9.51
Night	Fog	NIIRS 7.0	Group 4	2	85	80	32.42	7.66
Night	Fog	NIIRS 7.0	Group 4	3	91	90	0.03	6.56
Night	Fog	NIIRS 7.0	Group 3	1	32	16	25.19	6.16
Night	Fog	NIIRS 7.0	Group 3	2	59	56	32.01	8.21
Night	Fog	NIIRS 7.0	Group 3	3	68	66	24.25	7.10
Night	Fog	NIIRS 8.0	MQ-9	1	93	92	33.55	7.40
Night	Fog	NIIRS 8.0	MQ-9	2	98	98	25.58	5.80
Night	Fog	NIIRS 8.0	MQ-9	3	99	99	36.90	5.30
Night	Fog	NIIRS 8.0	Group 5	1	97	97	22.47	6.15
Night	Fog	NIIRS 8.0	Group 5	2	100	99	25.96	4.70
Night	Fog	NIIRS 8.0	Group 5	3	100	99	—	3.96
Night	Fog	NIIRS 8.0	Group 4	1	57	35	25.33	10.09
Night	Fog	NIIRS 8.0	Group 4	2	85	81	40.99	8.44
Night	Fog	NIIRS 8.0	Group 4	3	94	93	59.47	6.98
Night	Fog	NIIRS 8.0	Group 3	1	29	17	22.68	8.16
Night	Fog	NIIRS 8.0	Group 3	2	71	65	47.04	9.03
Night	Fog	NIIRS 8.0	Group 3	3	82	81	58.47	8.18

References

88th Air Base Wing Public Affairs, "Air Force Accepts Delivery of Final MQ-1 Predator," Wright-Patterson Air Force Base, Ohio, March 4, 2011. As of December 7, 2012: www.af.mil/news/story.asp?id=123245388

Bennett, Bart E., Joel Kvitky, Daniel M. Norton, and Michael Nixon, *MQ-1 Predator and MQ-9 Reaper Air-to-Ground Sensor Capabilities*, Santa Monica, Calif.: RAND Corporation, TR-1174-AF, 2013, Not available to the general public.

Deiters, Dalia, "RPA Program Brief," Air Force Special Operations Forces, April 7, 2011, Not available to the general public.

DoD—*See* U.S. Department of Defense.

Driggers, Ronald G., James A. Ratches, Jon C. Leachtenauer, and Regina W. Kistner, "Synthetic Aperture Radar Target Acquisition Model Based on a National Imagery Interpretability Rating Scale to Probability of Discrimination Conversion," *Optical Engineering*, Vol. 42, No. 7, 2003.

Imagery Resolution Assessments and Reporting Standards Committee, *Civil NIIRS Reference*, March 1996.

Irvine, John M., Ana Ivelisse Aviles, David M. Cannon, Charles Fenimore, Donna S. Haverkamp, Steven A. Israel, Gary O'Brien, and John Roberts, "Developing an Interpretability Scale for Motion Imagery," *Optical Engineering*, Vol. 46, No. 11, p. 117401, November 2007.

Joint Publication 3-60, *Joint Targeting*, Washington, D.C.: Joint Chiefs of Staff, April 13, 2007.

Leachtenauer, Jon C., William Malia, John Irvine, Linda Colburn, and Nanette Salvaggio, "General Image-Quality Equation: GIQE," *Applied Optics*, Vol. 36, No. 32, November 10, 1997.

Lingel, Sherrill, Lance Menthe, Brien Alkire, John Gibson, Scott A. Grossman, Robert A. Guffey, Keith Henry, Lindsay D. Millard, Christopher A. Mouton, George Nacouzi, and Edward Wu, *Methodologies for Analyzing Remotely Piloted Aircraft in Future Roles and Missions*, Santa Monica, Calif.: RAND Corporation, DB-637-AF, 2012. As of December 6, 2012:
http://www.rand.org/pubs/documented_briefings/DB637.html

Majumdar, Dave, "Air Force Orders Single Predator C Avenger," *Air Force Times*, December 13, 2011.

Menthe, Lance, and Jeffrey Sullivan, *A RAND Analysis Tool for Intelligence, Surveillance, and Reconnaissance: The Collections Operations Model*, Santa Monica, Calif.: RAND Corporation, TR-557-AF, 2008. As of December 6, 2012: http://www.rand.org/pubs/technical_reports/TR557.html

Motion Imagery Standards Board, *Recommended Practice: Video-NIIRS*, October 15, 2009, MISB RP 0901.

Northrop Grumman Corporation, "Raven Eye I: Unmanned Multi-Mission Stabilized Payload," factsheet, Falls Church, Va., DS-295-BAS-0803, undated a.

———, "Raven Eye II: Unmanned Multi-Mission Stabilized Payload," factsheet, Falls Church, Va., DS-296-BAS-0803, undated b.

Skolnik, Merrill I., *Radar Handbook*, 3rd ed., New York: McGraw-Hill, 2008.

U.S. Department of Defense, *Aircraft Procurement Plan Fiscal Years 2012–2041*, Washington, D.C., A-A78844C, March 2011a.

———, *Unmanned Systems Integrated Roadmap FY 2011–2036*, Washington, D.C., November 9, 2011b.

RAND PROJECT AIR FORCE

www.rand.org

$29.95

ISBN 978-0-8330-8397-5

RR-276-AF